# Empirical Studies in Behavioral and Development Economics

Johannes Eigner

Doctor of Philosophy

The University of Edinburgh
School of Economics

2018

# Declaration of Own Work

I declare that this thesis was written and composed by myself and is the result of my own work unless clearly stated and referenced. This thesis has not been submitted for any other degree or professional qualification.

The work presented in Chapter 2 is completed in collaboration with Liang Bai, Camille Boudot, and Andre Butler. My co-authors have agreed that this study can appear within this thesis, and that it represents a substantial contribution on my part. I carried out major parts of the empirical analyses and contributed to writing up the results. In particular, I built the data set to be used in the empirical model, conducted the main statistical analyses, and created the shapefile used for the geographical maps. Moreover, I solely contributed the analysis of the effect of improved access to financial services on crop choice in sections 2.5.2 and 2.5.3, and the interaction of access to financial services, production choices, and weather in sections 2.4.3 and 2.5.4.

Johannes Eigner
April 15, 2019

*to my wife Olga and my mother Christa*

# Acknowledgments

I am very grateful to my supervisors Ed Hopkins and Andy Snell for their continuous guidance throughout the years. I have learned a great deal from both of them. Ed has taken a keen interest in my work and supported me during my research. I also would like to thank Tatiana Kornienko and Liang Bai who provided me with useful comments whenever I needed to discuss my work.

I also wish to thank fellow PhD students for their support and helpful comments. In particular, I would like to thank Olga Eigner, Stuart Baumann, Tomasz Sulka, and Aspasia Bizopoulou. Furthermore, I am grateful to the PhD directors and administrative staff for making my PhD journey as smooth as possible. Also, I wish to thank the participants at annual SGPE Crieff conferences, in particular Mark Schaffer and Paul Allanson, for their comments and constructive criticisms.

# Abstract of Thesis

The chapters of this thesis comprise three separate studies on topics in behavioral and development economics. The first chapter discusses the impact of advantageous and disadvantageous income inequality on self-reported life satisfaction. The second chapter analyses the effect of access to financial services in rural India on agricultural outcomes. In the third chapter I introduce a new instrumental variable to identify the effect of peer expenditure on household consumption.

**Chapter 1. Spiteful Preferences or Inequality Aversion: What drives the Comparison Income Effect?** In this chapter I use happiness data to distinguish between spiteful and inequality averse preferences. Both are consistent with the Easterlin paradox but have quite different implications for the relationship between happiness and income inequality. Empirical evidence suggests that happiness is decreasing in the income of relevant others (i.e. comparison income). On its own, this relationship provides insufficient evidence to pin down the underlying preferences but a remedy is available. The simple comparison income model is nested in a more general utility function which accounts for several types of interdependent preferences. Using data from the German Socio-Economic Panel (SOEP) survey, I demonstrate that the full model has more predictive power than the reduced one. Moreover, aversion to income inequality appears to drive the comparison income effect. The results are robust to several alternative model specifications.

**Chapter 2. Rural Banks and Agricultural Production: Evidence from India's Social Banking Experiment** In this chapter, we study the effects of improved access to banking services on agricultural production in India. We exploit a series of policy rules during the 1980s to generate a time-varying instrument for rural branch expansion at the district level. We find that a 1% growth in rural banks increased aggregate yields by 0.4%. This effect is driven by an uptake in the cultivation of higher-yielding varieties of cereal crops, as well as an increase in the

area share allocated to cash crops. Banks also attenuate the effect of lagged rainfall on output, via changes in the use of irrigation.

**Consumption-savings decisions with interdependent preferences. Staying ahead or catching up?** In the third chapter, I estimate the effect of expenditure disparity on household consumption using a novel instrumental variable. In a life-cycle setting, households are assumed to care about the distance to others above and below them in the expenditure distribution. To solve the endogeneity problem arising from correlated and exogenous effects, I instrument expenditure disparity with the share of households who receive unexpected windfall income. Using SOEP data, the average household is found to have envious and prideful preferences in that growing disparity to those who spend more and reduction in the disparity to others who spend less is associated with consumption expenditure growth.

# Lay Summary

A large number of empirical studies find that the income of relevant others (i.e. comparison income) affects self-reported life satisfaction (i.e. happiness). Moreover, happiness and comparison income are found to be inversely related and it is often assumed that this implies happiness is also decreasing in income inequality. This is a logical fallacy. There are plausible models of relative concerns in which social standing matters and yet utility is increasing in inequality by reducing conspicuous consumption. The first chapter separates attitudes towards income inequality from comparison income effects. The standard model used to estimate comparison income effects is nested in a general utility framework that allows to distinguish between inequality aversion and competitive preferences. For this reason, it is easy to statistically compare the relative fit of both models. Using data from the German Socio-Economic Panel (SOEP), I find that the general model has significantly more predictive power than the reduced model. This is the first study to establish this result. To pin down the preferences underlying the comparison income effect, I estimate the marginal effects of individual specific advantageous and disadvantageous income inequality on happiness directly. Controlling for own income, individuals appear to be on average averse to both advantageous and disadvantageous income inequality. This result is important because it rules out other types of interdependent preferences (such as spiteful preferences) for the average individual, that are consistent with the comparison income effect and thereby reconciles empirical and experimental findings.

The marginal effect of income inequality on self-reported happiness is consistent across various exogenously determined subsets of relevant others (i.e. the reference groups) to whom individuals are assumed to compare. Consider reference groups defined according to occupation type, age-cohort and gender of the individual. Everything else being equal, a 100% increase in net real monthly income is associated

with a non-causal increase in reported life satisfaction of 19% of a standard-deviation. Holding own income fixed, an increase in the average income distance to better-off others by EUR 1,000 is associated with a reduction in reported satisfaction by approximately 7% of a standard-deviation. This result suggests that an increase in monthly income of the average individual by 100% does not change perceived well-being, if at the same time the average distance to richer individuals' monthly income increases by approximately EUR 2,500. The negative effect of advantageous income inequality is relatively smaller. An increase in the average income distance to worse-off others by EUR 1,000 reduces satisfaction by approximately 2% of a standard-deviation of self-reported life satisfaction. Therefore, a 100% increase in income is predicted to leave happiness unchanged, if at the same time the average monthly income distance to poorer individuals increases by approximately EUR 11,000 –an unrealistically large amount given the average net deflated income of about EUR 1,700. This suggests that individuals are on average averse to disadvantageous and, to a lesser extend, advantageous income inequality. The outcomes do not appear to be driven by estimation methodology.

Evidence from game-theoretic experiments suggests that there is considerable heterogeneity among attitudes towards payoff inequality. To account for some of this heterogeneity, I estimate attitudes towards income inequality conditional on observable characteristics such as age-cohort, gender, residency in the states of the former GDR, and self-reported political conviction. Both relatively young and old individuals are on average more averse to advantageous income inequality than the comparison cohort. While both genders appear to be negatively affected by advantageous income inequality, disadvantageous income inequality affects men more strongly. In all specifications, the results imply that Eastern Germans are on average more averse to income inequality than Western Germans. Given the communist past of the former GDR, this result suggests that interdependent preferences in a society are influenced by norms. Consistent with these findings, politically left-leaning individuals are found to be more strongly affected by income inequality than rightists or centrists. On the other hand, right-leaning individuals appear to have upward looking preferences in that they are not affected by changes in the income distance to worse-off others.

In the second chapter my co-authors and I study the effect of access to financial services on agricultural outcomes. Improving access to formal banking and financial services has long been seen as a key tool to reducing poverty in developing countries.

Recent empirical research has shown its effectiveness in this regard –also in India. Despite this, we know relatively little about the underlying pathways through which access to banks can lead to reductions in poverty. In this paper, we use district-level panel data to study India's government-led rural banking program in the 1980s to shed light on these potential pathways, focusing on agricultural production. Access to banking services has the potential to increase agricultural productivity, and thereby rural incomes, via three leading pathways. First, such services may help individual farmers to overcome liquidity constraints, which can cause under-usage of inputs. We investigate this by analyzing the impact of bank growth on agricultural yields, as well as the use of inputs including land, irrigation, seeds, fertilizers and machinery. Second, bank credit can help improve intertemporal consumption smoothing, and therefore increase farmers' willingness to engage in riskier but more profitable activities. We assess this potential channel by considering changes in crop portfolio over time in response to bank growth, specifically shifts towards more volatile but higher return crops. Third, banks can provide some insurance against adverse weather shocks. To test for this, we examine whether banks attenuate the relationship between lagged rainfall and contemporaneous production.

Our results show that improved access to banks did significantly increase agricultural yields and production. Specifically, a 1% growth in banks is associated with a 0.4% growth in yields. To decompose this relationship further, we document an increase in the use of relatively more expensive but higher-yielding variety (HYV) seeds for cereal cultivation. Moreover, bank growth appears to shift the overall portfolio towards more cash crops and double-cropping during the winter season. Finally, we find banks had an attenuating influence on the negative effects of lagged rainfall shocks through changes in the use of irrigation resources. Evaluating the causal impacts of formal banking services on agricultural production in a non-experimental setting is challenging. For example, banks may choose to open new branches in the most productive regions at baseline, but lower growth potential, leading OLS to underestimate the true effects. In contrast, banks may choose to open new branches in regions with lower baseline productivity, but higher growth potential, leading OLS to overestimate the true effects. In order to address these potential biases, we exploit a series of central-government regulations, aimed explicitly at expanding the rural banking infrastructure in India during the 1980s, to generate a time-varying instrument for bank growth at the district level.

From 1978 to 1990, three consecutive periods of Branch Licensing Policies (BLPs) guided the spread of banking infrastructure in India. Instigated to ensure a more equitable distribution of banking facilities across the country, the BLPs regulated the location of new branches towards unbanked regions. Using a target population-per-branch ratio (set to the national average at the onset of each period), a district was identified as deficit if found to be above the stipulated threshold. If classified as such, the district was assigned a detailed branch expansion program. Compliance was monitored at the end of each period, when districts were reclassified based on their updated population-per-branch ratio. Our identification strategy leverages the fact that the same district can be deficit in one period, and non-deficit another. Such policy-induced changes in bank growth within a district over time allows us to estimate more accurately the causal impacts of this major expansion in banking infrastructure in 20$^{\text{th}}$ century India. To test the validity of this empirical strategy more formally, we carry out a number of placebo tests that show the instrument to be uncorrelated with potentially confounding factors such as growths in physical infrastructure (namely road networks), market development, other government policies such as preferential lending to agriculture. Furthermore, we show that the instrument is uncorrelated with pre-trends in our outcomes.

The third chapter is dedicated to measuring the effect of expenditure disparity on household consumption choices. Status seeking and habit formation are important characteristics of human behavior. A growing number of empirical studies account for inter-household comparisons and find measurable effects on consumption choices. The empirical results are typically obtained from exploiting restrictions placed on the optimal consumption path. The utility function accounts for relative concerns with respect to a predefined reference group. The crucial problem with the identification of peer effects models of this type is related to the reflection problem of Manski (1993): A priori, it is difficult to distinguish the endogenous effect of peer expenditure on household consumption from unobserved exogenous and correlated effects. Inconsistency from exogenous peer effects arises if members of the reference group share characteristics that affect their consumption choice in a similar manner. For example, the age cohort of households may be a determinant of reference group affiliation which also affects expenditure profiles. If the households in a reference group face disturbances that affect their expenditure in a similar way due to common unobservable traits, the peer effects model is inconsistent due to correlated effects. For example, regional fluctuations and economic growth may affect permanent incomes and thereby expenditures within a reference group in a similar way.

To account for the reflection problem, I instrument expenditure disparity with the share of households in the reference group who receive windfall income. Here, windfall income is defined as unexpected income gain from inheritances, gifts, or lottery wins above EUR 2,500. To the best of my knowledge, this is the first paper that makes use of unexpected income shocks from inheritances, gifts, and lottery wins as an instrumental variable for average expenditure disparity.

To pin down the direction of comparisons, I decompose the effect of average peer expenditures into disparity to those with higher (i.e. disadvantageous disparity) and lower (i.e. advantageous disparity) expenditures. Interdependent preferences may be characterized by upward or downward comparisons in that only the expenses of households above or below in the expenditure distribution matter to the household who makes the comparison. The results indicate that expenditure growth is positive in the distance to others higher up in the distribution. Likewise, increases in the distance to households with lower expenditure lead to reduced household expenditure. The relative size of these effects varies across reference group specifications. For reference groups defined by education, age-cohort, and cohabitation status, a 1% increase in disadvantageous disparity is related to an increase in household consumption of approximately 0.2% Likewise, an increase in advantageous disparity by 1% is related to a decrease in household consumption by approximately 0.22%.

# Contents

# List of Figures

# List of Tables

# Chapter 1

# Spiteful Preferences or Inequality Aversion: What drives the Comparison Income Effect?

## 1.1 Introduction

A large number of empirical studies find that the income of relevant others (i.e. comparison income) affects self-reported life satisfaction (i.e. happiness) scores[1]. Moreover, happiness and comparison income are found to be inversely related and it is often assumed that this implies happiness is also decreasing in income inequality. However, as Hopkins (2008) notes, this is a logical fallacy. There are plausible models of relative concerns[2] in which social standing matters and yet welfare is increasing in inequality by reducing conspicuous consumption. This chapter disentangles attitudes towards income inequality from comparison income effects. The standard model used to estimate comparison income effects is nested in the more general Fehr and Schmidt (1999) (henceforth F&S) utility framework. It therefore is easy to statistically compare the relative fit of both models. Using data from the German Socio-Economic Panel (SOEP), I find that the F&S model has significantly more predictive power than the comparison income model. This is the first paper to establish this result. To pin down the preferences underlying the comparison income

[1] see for example van de Stadt et al. (1985); Clark and Oswald (1994); McBride (2001); Senik (2004); Ferrer-i-Carbonell (2005); Luttmer (2005); Clark et al. (2008). Clark and Senik (2010) summarize the existing literature.

[2] See for example Hopkins and Kornienko (2004) for a model of status competition in which greater equality leads to welfare-reducing conspicuous consumption.

effect, I estimate the marginal effects of individual specific advantageous and disadvantageous income inequality on happiness directly. Controlling for own income, individuals appear to be on average averse to both advantageous and disadvantageous income inequality. This result is important because it rules out other types of interdependent preferences that are consistent with the comparison income effect and thereby reconciles empirical and experimental findings.

The marginal effect of income inequality on self-reported happiness is consistent across various specifications. Consider reference groups defined according to occupation, age-cohort and gender. Everything else equal, a 100% increase in net real monthly income is associated with an non-causal increase in reported life satisfaction of 19% of a standard-deviation. An increase in the average income distance to better-off others by EUR 1,000 decreases reported satisfaction by approximately 7% of a standard-deviation. Keeping everything else equal, this result suggests that an increase in monthly income of the average individual by 100% does not change perceived well-being, if at the same time the average distance to richer individuals' monthly income increases by approximately EUR 2,500. The negative effect of advantageous income inequality is smaller but significant. An increase in the average income distance to worse-off others by EUR 1,000 reduces satisfaction by approximately 2% of a standard-deviation of self-reported life satisfaction. Therefore, a 100% increase in income does not change reported satisfaction, if at the same time the average monthly income distance to poorer individuals increases by approximately EUR 11,000 –an unrealistically large amount given the average net deflated income of about EUR 1,700. This suggests that individuals are on average averse to disadvantageous and, to a lesser extend, advantageous income inequality. The outcomes do not appear to be driven by estimation methodology. Compared to ordinary least squares, the results do not change substantially when ordered probit or ordered logit estimators with fixed effects are employed.

Evidence from game-theoretic experiments suggests that there is considerable heterogeneity among attitudes towards payoff inequality. To account for some of this heterogeneity, I estimate attitudes towards income inequality conditional on observable characteristics such as age-cohort, gender, residency in the states of the former GDR, and self-stated political conviction. Both relatively young and old individuals are on average more averse to advantageous income inequality than the comparison cohort. While both genders appear to be negatively affected by advantageous income inequality, disadvantageous income inequality affects men more strongly. In all specifications, the results predict that Eastern Germans are on average more averse to income inequality than Western Germans. Given the communist past of the former GDR, this result supports the view that interdependent preferences are influenced by societal norms. Consistent with these findings, politically left-leaning individuals are more strongly affected by income inequality than rightists or centrists. On the other hand, right-leaning individuals appear to have upward looking preferences in that they are not affected by changes in the income distance to worse-off others.

A potential threat for the identification of interdependent preferences regarding reference group income is related to the reflection problem of Manski (1993). The problem arises if a researcher observing the distribution of behavior in a population tries to infer whether the average behavior in some group influences the behavior of the individuals within that group. Similar behavior within a group may be due to the interaction of the group members (endogenous effect), driven by common exogenous traits of the group members (exogenous effect), or due to common unobservable characteristics or similar institutional environments (correlated effect). Attitudes towards income inequality may be correlated with the specified reference groups. In experimental studies, the reference group for each individual is generally assumed to be other participants in the experiment. In household survey data the relevant comparison group is unobserved. Obtaining reference groups from observed behavior will make any social effects model hold tautologically. Therefore, I define reference groups by observable demographic characteristics. Clark and Senik (2010) report that incomes are most often compared to those of work colleagues, friends, and family members. Following the comparison income literature, reference groups are based on age-cohort, occupation type, educational attainment, gender, and cohabitation with a life-partner. The results do not change qualitatively between reference group specifications. Following Drechsel-Grau and Schmid (2014), for each individual the respective reference group includes similar others not living in the same state (*Bundesland*) to control for correlated effects originating from institutional environments. Furthermore, I include state-year interactions to control for time-varying regional shocks. Similar to Maurer and Meier (2008), I account for exogenous effects by including socio-demographic measures of the reference groups as additional regressors. Last, reference group indicator variables are included alongside year and individual fixed effects to capture stratification effects and unobserved heterogeneity.

The response rate for most variables is close to 100%. In the eleven years of data, the majority of missing values stem from the dependent variable *self-reported* *happiness*. Missing values, especially in the dependent variable could be a source of inconsistency if the observations are not missing randomly. For example, one can assume that respondents who are particularly unhappy about their income or status in society would decide not to reveal their unhappiness out of shame or pride. Indeed, for all years, the average income of respondents to the question on happiness is significantly larger than the average income of non-respondents. In this case, a negative effect of disadvantageous income inequality on self-reported happiness would be underestimated in the empirical model. Ultimately, this data problem is beyond the scope of this study.

This chapter is closely related to work of D'Ambrosio and Frick (2012) and Cojocaru (2014). The first authors study the effects of changes in relative deprivation and satisfaction on self-reported happiness in a dynamic framework using SOEP data. They find that an individual's happiness is affected negatively by the comparison to richer others and affected positively by the comparison to those who are poorer. Their estimates on income dynamics suggest the presence of newly richer and poorer individuals plays the informational role described by the tunnel effect of Hirschman (1973). My findings contradict their results –instead of spiteful preferences, I find inequality aversion. The discrepancy in results is likely caused by differences in the empirical model. The main difference is that D'Ambrosio and Frick (2012) take the entire sample population as the relevant reference group and hence do not include socio-demographic aggregates to account for exogenous effects.

It could be argued that the relevant reference income distribution is best represented by including all incomes. A major drawback to this approach is that due to exact collinearity, time effects can not be included in their specification to mitigate omitted variable bias from correlated effects[3]. Consequently, both aggregate life satisfaction and income inequality may be affected by economic growth which enters the error term. Furthermore, as Clark and Senik (2010) show, the relevant comparison group likely depends on individual characteristics such as occupation, age, education, and region of residency. By computing income inequality within reference groups defined by several individual specific characteristics, I extend existing work on comparison income effects which generally employs only a single reference group specification.

[3]D'Ambrosio and Frick (2012) claim that they account for time effects but it is easy to see that the measures of income and income disparity are linearly related to time fixed effects and hence cannot be included in their empirical model.

Cojocaru (2014) estimates a rearranged F&S model using data from the *Life in Transition* survey and reference groups defined by geographic region. He finds that individuals exhibit aversion to income inequality, a result that cannot be captured by the Gini index. This finding is in line with my results. The Life in Transition survey has broad geographic coverage including 27 countries, but does not contain longitudinal data. Therefore, the results solely rely on variation between instead of within individuals. With cross-sectional data, accounting for unobserved heterogeneity across reference groups by means of reference group fixed effects is not possible due to exact collinearity. Therefore, the threat of omitted variable bias from correlated or exogenous effects cannot be mitigated. Another potential problem in his analysis is the small number of individuals per reference group. The size of the reference group within a Census Enumeration Area is ranging between 14 to 25 observations. As a robustness check, the author extends the regions accross which reference groups are defined to include an average of 150 individuals per group. While the increased number of observations allows for a more meaningful estimation of regional income distributions, it comes at the cost of weakening the claim of observability which underlies the concept of relative deprivation and relative satisfaction. Different to Cojocaru (2014), my results rely on a longitudinal data set which contains approximately the same number of individuals per year as the Life in Transition survey as a whole, while being geographically restricted to one country instead of 27.

The remainder of this chapter is structured as follows. The theoretical model is described in Section 1.2. Rearranging the F&S model reveals that it nests the comparison income model which allows for a simple statistical test of predictive power between both models. Section 1.3, summarizes the empirical strategy and describes the reference groups by which the inequality measures will be calculated. Section 1.4 briefly describes the data. The results are presented in Section 1.5. I demonstrate that the F&S-model has significantly more predictive power than the simple relative income model. Furthermore, it is inequality aversion that drives the comparison income effect in most specifications. For many reference group specifications, the results are robust to estimation methodology, relaxing the linearity assumption of the inequality measures, and when the model is computed for subsets of the sample. Section 1.6 concludes.

## 1.2 Theoretical framework

The utility function with interdependent preferences introduced by F&S to account for deviations from game-theoretic predictions in experiments with $N$ individuals and without predefined reference groups is given by:

$$U_i(x) = x_i + \alpha_i \frac{1}{N-1} \sum_{x_j > x_i} (x_j - x_i) + \beta_i \frac{1}{N-1} \sum_{x_i > x_j} (x_i - x_j), \tag{1.1}$$

where $x_i \geq 0$ is individual $i$'s payoff. The second term measures attitude towards disadvantageous payoff inequality and the third term attitude towards advantageous payoff inequality, both from the perspective of $i$. The parameters $\alpha_i$ and $\beta_i$ define the nature of individual $i$'s preferences. If $\alpha_i = \beta_i = 0$, the utility specification reduces to a linear function of own payoff without interdependent preferences. If $\alpha_i < 0$ and $\beta_i < 0$, individual $i$ is averse to payoff inequality[4]. An individual with spiteful preferences can be modeled by setting $\alpha_i < 0 < \beta_i$. This parameter relation would imply that individual $i$ is averse to disadvantageous payoff inequality but prefers a growing payoff-distance to others poorer than her. Assume for the remainder of this chapter that equation (1.1) not only applies to payoffs in experiments, but more generally reflects attitudes towards income inequality with respect to a reference group.

Define the inequality measures $D_i(x) = 1/(N-1) \sum_{x_j > x_i} (x_j - x_i)$ and $S_i(x) = 1/(N-1) \sum_{x_i > x_j} (x_i - x_j)$. For simplicity, F&S impose the assumption that payoff inequality enters the utility function linearly. Using net deflated monthly income instead of payments received in experiments, it could be argued that income differences have a non-linear impact on perceived income inequality. For example in a society with two individuals, if the wealth difference between the two doubles, it is possible that the poorer individual perceives more, or less than twice the initial level of deprivation. Let $g^+$ and $g^-$ represent income-difference dependent weighting functions on the inequality measures $D_i$ and $S_i$ respectively. The inequality measures linear in income can be written as $D_i(x) = D_i(x) g_0^+$ and $S_i(x) = S_i(x) g_0^-$ for constant weights $g_0^+ = g_0^- = 1$. The weighting function $g_1^+(x) = \sum_{x_j > x_i} \ln(x_j - x_i) / \sum_{x_j > x_i} (x_j - x_i)$, decreasing in $(x_j - x_i)$, is equivalent to using logarithmic income differences in the calculation of the inequality measures. In effect, small income differences enter the

[4]For inequality averse preferences, F&S further impose the plausible condition that $\alpha_i \leq \beta_i < 0$ which implies that disadvantageous inequality affects utility at least as strongly as advantageous inequality.

utility function with a relatively larger weight. This specification imposes the assumption that smaller income differences are more visible or important than larger ones. This assumption is in line with the predictions from models of status competition where closer proximity of individuals in the status dimension increases wasteful conspicuous consumption. The weighting function $g_2^+(x) = \sum_{x_j > x_i}(x_j - x_i)$, increasing in $(x_j - x_i)$, is equivalent to squaring the income differences and thereby imposes the assumption that large income differences have a relatively stronger impact on perceived inequality than smaller ones. It can be argued that large income differences create a feeling of deprivation and skepticism regarding social mobility. On the other side, those with very high incomes may feel guilt and concern about social cohesion. Since it is not unequivocally clear which weighting function should be chosen for $D_i$ and $S_i$, I employ the two exemplary weighting functions in the empirical analysis alongside the linear model to verify robustness.

Deaton (2003) shows for linear weights and continuous distributions[5] of $x$ that (1.1) can be rearranged:

$$U_i(x) = \left(1 + \beta_i \frac{N}{N-1}\right) x_i - \beta_i \mu_i(x_{-i}) + (\alpha_i + \beta_i) D_i(x). \tag{1.2}$$

The measure of advantageous income inequality, $S_i(x)$, can be expressed by the variables $x_i$, $D_i(x)$, and $\mu_i(x_{-i}) = 1/(N-1)\sum_{j \neq i} x_j$. The latter variable represents the average income of others (i.e. comparison income). It is a robust empirical finding that self-reported happiness is decreasing in the income of similar others. Equation (1.2) is important because it shows that the standard comparison income model is nested in the F&S model. Assuming linearity, this allows to test and compare the predictive power of both models.

In much of the empirical literature the negative relationship between comparison income and happiness is taken as suggestive evidence of inequality averse preferences (Clark et al., 2008). However, other types of interdependent preferences are coherent with a negative comparison income effect. Suppose the average individual has spiteful preferences in that she obtains utility not only from absolute income but also from getting ahead of those with lower income and catching up with those who are richer. A regression of self-reported happiness on income and comparison income would yield a negative coefficient independent of changes in income inequality. To see this, assume individuals have F&S-type preferences as represented in equation (1.2). For

[5] Appendix A shows the steps in the derivation for discrete distributions.

simplicity, assume the preferences of the average person are either spiteful so that $\alpha_i < 0 < \beta_i$ or inequality averse with $\alpha_i < \beta_i < 0$. A researcher interested in the effect of peer income $\mu_i(x_{-i})$ on happiness $U_i$ specifies the simplified empirical model:

$$\begin{aligned} U_i &= \gamma_0 + \gamma_1 x_i + \gamma_2 \mu_i(x_{-i}) + Z_i \zeta + \nu_i \\ \nu_i &= \gamma_3 D_i(x) + \varepsilon_i \qquad , \end{aligned} \tag{1.3}$$

with control variables $Z_i$ where by assumption $\gamma_1 = 1 + \beta \frac{N}{N-1}$, $\gamma_2 = -\beta$ and $\gamma_3 = \alpha + \beta$. In other words, a reduced form of equation (1.2) is estimated with the restriction $\alpha + \beta = 0$. In a special case of spiteful preferences such that $\alpha = -\beta$, the restriction may be fulfilled. In this case, $\gamma_2$ will be negative since income gains of others reduce utility. Assume now that the restriction is violated and individuals are inequality averse. Then, $\gamma_2$ is expected to be positive but may be affected by omitted variable bias since $D_i(x)$, $x_i$, and $\mu(x_{-i})$ are functionally related. $D_i(x)$ enters the error term $\nu_i$ with a negative sign as long as $\alpha < \beta < 0$. In Appendix A I show that $\mathrm{Cov}[\mu_i(x_{-i}), D_i(x)] > 0$ for non-degenerate income distributions which implies larger values of comparison income are associated with larger values for disadvantageous inequality and vice versa.

Since $D_i(x)$ enters the error term with a negative sign, the coefficient on comparison income would be downward biased and potentially negative even if the average individual is averse to income inequality. Using panel instead of cross-sectional data will not mitigate this bias. However, by allowing for F&S-type preferences instead of imposing the restriction $\alpha + \beta = 0$, it is possible to distinguish the underlying type of interdependent preferences. Extending equation (1.3) to nest the F&S utility framework gives:

$$U_i = \gamma_0 + \gamma_1 x_i + \gamma_2^* \mu_i(x_{-i}) + \gamma_3 D_i(x) + Z_i \zeta + \varepsilon_i, \tag{1.4}$$

where $\gamma_2^* = -\beta$. A t-test on $\gamma_3$ allows to compare the predictive power of both models if $\alpha \neq 0$ and $\beta \neq 0$ do not sum to zero. Depending on the relative explanatory power of comparison income alone and more general interdependent preferences, the estimated parameters can be interpreted as described in Table 1.1.

A positive estimate of $\gamma_2^*$ and $\gamma_3$ implies selfless or altruistic preferences in the F&S model where utility increases in the income distance to richer others decreases in the income distance to poorer others. With observational data, it is more plausible that peer group income changes contain information about own future advances. Positive

Table 1.1: Implications of point estimates for underlying preferences.

| | $\gamma_3 > 0$ | $\gamma_3 < 0$ | $\gamma_3 = 0$ |
|---|---|---|---|
| $\gamma_2^* > 0$ | altruistic preferences ($\beta < 0 < \alpha$) | inequality aversion if $\lvert\gamma_3\rvert > \lvert\gamma_2^*\rvert$ then $\alpha < \beta < 0$ | positive comparison income effect (or $\alpha = -\beta$) |
| $\gamma_2^* < 0$ | pro-inequality/ spiteful preferences | spiteful preferences Hopkins and Kornienko (2004) | negative comparison income effect (or $\alpha = -\beta$) |
| $\gamma_2^* = 0$ | tunnel effect Hirschman (1973) | upward comparisons Duesenberry (1949) | no interdependent preferences |

estimates of $\gamma_2^*$ and $\gamma_3$ are therefore considered evidence in favor of the tunnel effect (Hirschman, 1973). If $\gamma_3 = \gamma_2^* = 0$, peer incomes do not affect utility. In column (3), a positive comparison income effect may indicate either $\beta < 0$ and $\alpha = -\beta$ –a special case of tunnel effect preferences, or that there is no differential effect of the income distance to richer peers beyond the comparison income effect. A negative comparison income effect on the other hand indicates spiteful preferences where $\alpha$ and $\beta$ sum to zero or that the F&S model is inferior to the reduced model. In both cases, I regard $\gamma_3 = 0$ as strong evidence in favor of the comparison income model.

In case $\gamma_3 \neq 0$ the sign and size of the theoretical parameters underlying the coefficients informs about the type of preferences. For example, spiteful preferences similar to Hopkins and Kornienko (2004) are evident if $\alpha < 0 < \beta$. Some studies find that comparisons are mostly upwards (Ferrer-i-Carbonell, 2005). If $\gamma_2^* = 0$, the sign of $\gamma_3$ allows to distinguish between the tunnel effect ($\alpha > 0$) and upward-looking comparisons ($\alpha < 0$) as postulated by Duesenberry (1949). Last, $\gamma_2^* > 0$ and $\gamma_3 < 0$ imply aversion to both advantageous and disadvantageous income inequality.

## 1.3 Empirical Strategy

The empirical analysis will be based on a subjective self-reported measure of life satisfaction obtained from individual responses to the following SOEP survey question:

> *"And finally, we would like to ask you about your satisfaction with your life in general. Please answer by using the following scale, in which 0 means totally unhappy, and 10 means totally happy. How happy are you with your life as a whole?"*

The answers to this question take on discrete values on a 11-point scale. Assume that (1) individuals are willing and able to answer, (2) the answers are a positive monotonic transformation of the underlying metaphysical concept of utility, (3) the answers are interpersonally cardinally comparable. Ferrer-i-Carbonell and Frijters (2004) find that assuming ordinal or cardinal comparability makes little difference as long as individual-specific heterogeneity in responses is accounted for. This suggests that Panel data and fixed effects models should be used. The preferred empirical specification is an ordered latent response model that controls for time invariant heterogeneity while not requiring cardinal comparability. Unfortunately due to the incidental parameters problem, standard ordered probit and logit models with fixed effects are biased with large $N$ and small $T$. A feasible alternative is transforming the happiness measure to a binary variable indicating responses above and below average and using probit fixed effects (Chamberlain, 1980). Since this model restricts analysis to individuals who cross the cut-off, there is a large loss of data. Assuming the correlation between time-invariant unobservables and the included regressors is linear in the averages of the latter (Mundlak, 1978) this data loss can be prevented. Alternatively, Baetschmann et al. (2015) propose an ordered logit fixed effects estimator (BUC) which appears to be immune to small sample bias compared to other consistent estimators. To ensure that the outcomes are not driven by imposing interpersonal cardinal comparability, additionally to ordinary least squares, results from the ordered probit and logit fixed effects estimators described above are reported.

Assume that for every individual with interdependent preferences the assessment of personal advantageous and disadvantageous income inequality depends on how her income compares to relevant others –her reference group. If reference groups are endogenous, group affiliation likely depends on occupation and demographic characteristics. According to Clark and Senik (2010), approximately 35% of respondents to the European Social Survey stated that they do not compare their income to others. Those who compare their income name work colleagues (56%), friends (23%), family members (9%), and undefined others (12%) as their reference group. It can be argued that individuals compare their own standing to a group similar to them, a group they aspire to belong to in the future, their own income history, or a subset of the entire society perceived as representative for the region or country. In the empirical literature, reference groups are defined either across individuals who share observable characteristics, within the same occupations, or by regions to capture the regional specific income distribution observed by the individual.

A potential obstacle for the identification of interdependent preferences regarding peer income is related to the reflection problem of Manski (1993). The problem arises if a researcher observing the distribution of behavior in a population tries to infer whether the average behavior in some group influences the behavior of the individuals within that group. Similar behavior within a group may be due to the interaction of the group members (endogenous effect), driven by common exogenous traits of the group members (exogenous effect), or due to common unobservable characteristics or similar institutional environments (correlated effect). My goal is to identify endogenous effects of distributional changes on self-reported happiness. A source of bias could be that individuals in certain occupations may be affected differently by the incomes of their peers (exogenous effect), potentially due to differences in income transparency. Alternatively, if groups are based on observable demographics such as education, there is an exogenous effect if attitudes towards inequality vary with the socio-economic composition of the reference group. Additionally, there may be regional or institutional effects present that affect both self-reported happiness and inequality measures. For example, economic growth may affect self-reported happiness and incomes in a reference group in a non-linear way. To account for these identification problems, I define four reference groups by socio-demographic characteristics and compare results across specifications. Following Drechsel-Grau and Schmid (2014), for each individual the reference groups include similar others not living in the same state to control for correlated effects from institutional environments. Furthermore, state-year interactions are included to control for time-varying regional shocks. Similar to Maurer and Meier (2008), exogenous effects are accounted for by including socio-demographic measures of the reference groups as additional regressors. More specifically, all of the socio-demographic control variables such as age, years of education, number of children and adults in the household, are aggregated by individual-specific reference group and included as further regressors. Last, reference group indicator variables are included alongside year and individual fixed effects.

Since SOEP survey respondents are not asked whom they compare to, the individual specific reference group cannot be identified directly from the data. Furthermore, as shown by Manski (1995), obtaining reference groups from observed behavior will make any social effects model hold by construction and thwart identification. Therefore, informed specification of the relevant reference groups is required and will be based on observable demographic characteristics. Specifically, reference groups are defined according to (i) occupation-age-gender (ii) occupation-age-cohabitation,

(iii) education-age-gender, and (iv) education-age-cohabitation. Co-workers are the most frequently cited reference group. In specifications (i) and (ii) the measures of income inequality are calculated by the ten major occupation groups specified by the International Standard Classification of Occupations (ISCO)[6]. The age-cohorts are defined by individuals being younger than 25, between 25 and 35, between 35 and 45, between 45 and 65, and over 65 years old at the time of the interview. Cohabitation indicates whether the individual is living together with a life partner. The first and second specification results in 100 separate reference groups. In specifications (iii) and (iv), individuals are categorized into groups dependent on whether they reported less than 10, 10, 11, 12, or more than 12 years of education[7]. Combined with five age cohorts and gender or cohabitation, this results in a total of 50 reference groups. When occupation is used as a stratifying variable, the sample is restricted to employed individuals. If information on less than 100 individuals is available for a given year from the sample, the respective reference group is omitted for that year to achieve representative income distributions.

Instead of individual utility $H^*$, the discrete, ordered, categorical variable $H$ is observed. Assume the latent variable $H^*$ is related to income $x_{it}$, the aggregate income distance to others with higher and lower income in reference group $p$ and a vector of demographic control variables $Z$ as described in the baseline model:

$$\begin{aligned} H^*_{it} &= \delta_1 x_{it} + \alpha_2 D_{ipt}(x) + \beta_3 S_{ipt}(x) + \sum_j \zeta_j Z_{jit} + \sum_j \xi_j K_{-i,jt} + \nu_{it} \\ \nu_{it} &= \eta_i + \pi_p + \lambda_t + state_i \times t + \varepsilon_{it}, \end{aligned} \tag{1.5}$$

where $\eta_i$ and $\pi_p$ represent individual and group fixed effects respectively. Year effects are captured by $\lambda_t$ and $state_i \times t$ indicate state-year interactions. The vector of control variables $Z_{jit}$ contains *age*, *age-squared*, *years of education*, *number of children and adults living in the household*, whether the individual is currently *living with a*

[6]ISCO groups occupations mainly on the basis of the similarity of skills required to fulfill the tasks and duties of the jobs. The following 10 occupation types form reference groups: (1) legislators, senior officials and managers; (2) professionals; (3) technicians and associate professionals; (4) clerks; (5) service workers and shop and market sales workers; (6) skilled agricultural and fishery workers; (7) craft and related trades workers; (8) plant and machine operators and assemblers; (9) elementary occupations; (10) armed forces.

[7]Less than 10 years of school implies that the highest possible degree obtained is a *Hauptschulabschluss*. 10 and 11 years of schooling are required to achieve a *Realschulabschluss*. After 12 years of school, the *Abitur* can be achieved, which enables enrollment for tertiary education.

*partner*, *employment status*, *number of interviews*[8], and an indicator variable for *windfall profits*. $K_{-i,jt}$ contains the control variables specified in $Z_{jit}$ aggregated at the reference group level. $D_{ipt}(x)$ and $S_{ipt}(x)$ are calculated with respect to $i$'s exogenously defined reference group $p$. In some specifications, non-linear income difference dependent weights will be applied to the inequality measures.

Identification requires either within-reference-group variation of income or between-reference-group variation of mean income. Between variation implies that the within reference group income distribution is different to the population income distribution for some $p$ to avoid exact collinearity. This condition is generally fulfilled for reference groups defined according to similar occupation, age-cohort, education level, gender, and, cohabitation. Within group variation of income implies that despite sharing similar characteristics, individuals in the same reference group have different incomes so that the measures of income inequality are non-zero.

The special case of the rearranged F&S model with linear weighting functions will be used for testing the comparison income effect:

$$\begin{aligned} H^*_{it} &= \gamma_1 x_{it} + \gamma_2 \mu_{-ipt}(x) + \gamma_3 D_{ipt}(x) + \sum_j \zeta_j Z_{jit} + \sum_j \xi_j K_{-i,jt} + \nu_{it} \\ \nu_{it} &= \eta_i + \pi_p + \lambda_t + state_i \times t + \varepsilon_{it}, \end{aligned} \tag{1.6}$$

where the parameter estimates can be interpreted as described in Table 1.1. Model (1.5) is used instead of (1.6) to assess attitudes to income inequality for three reasons. First, model (1.5) allows for non-linear weighting functions. Second, attitudes towards income inequality may differ across individuals. Model (1.5) is better suited to test for differential effects of income inequality since the parameters of interest are estimated separately. Third, for some parameter values, the underlying preferences are unidentified in the rearranged model.

## 1.4 Data

I use household survey data from the German Socio Economic Panel (SOEP) to disentangle the preferences underlying the comparison income effect. Of all household surveys, the SOEP contains the longest series of happiness data and a large number of individuals. The populations in East and West Germany likely differ in attitudes

[8]Landua (1992) finds that experienced survey participants tend to avoid extreme answers.

towards income inequality due to their separate history. Individuals who grew up and live in the formerly communist GDR may be affected more strongly by income inequality in the society than those who experienced the social market economy. Nevertheless, the East Germany subsample is included together with the sample of West Germans in the regression and differences between east and west are accounted for by interaction terms. Data on income and happiness is available for the years 1984 until 2012 for West Germany and from 1990 to 2012 for East Germany. To compromise between avoiding spillovers from the German reunification in 1990 while having a rich data set, the analysis will be restricted to the years from 2002 to 2012 and to all individuals with German nationality. The main reason to choose this period is that it allows to include a subsample of high income households, added in 2002, to improve representativeness of the reference group income distributions.

The response rate for most variables is close to 100%. In the eleven years of data, the majority of missing values stem from *overall happiness* (25.5%) and *years of education* (27.0%). These values are stable over years and across subsamples. Missing values, especially in the dependent variable could be a source of inconsistency if the observations are not missing randomly. For *overall happiness* for example, one can assume that respondents who are particularly unhappy about their income or status in society would decide not to respond to this question. Indeed, a t-test for mean difference strongly rejects that the sample income averages of respondents and non-respondents to the happiness question are identical. For all years, the average income of respondents to the question on happiness is significantly larger than the average income of non-respondents. Ultimately, this data problem is beyond the scope of this study.

The self-centered payoff inequality measures are computed from deflated monthly net household income. To adjust for family size, income is divided by the square root of the number of household members. The analysis is conducted at the individual level. The measures for advantageous and disadvantageous inequality are calculated with respect to members in the four reference groups. The summary statistics for the inequality measures for all reference groups and with linear weighting functions are reported in Table 1.2. The data contains information on 34,380 individuals over on average 5.6 years, yielding a total of 192,669 observations. Approximately 47.7% of the sample population is male, 26.2% are residing in the states of the former GDR, and 60.6% are employed[9]. The binary control variable *Interviews* indicates experienced survey respondents who where interviewed at least three times. *Cohabitation* indicates if the person is currently living with his or her life partner. The variables *Adults* and *Children* denote respectively the number of adults and children living in the household. *Education* measures the years of completed primary, secondary, and tertiary education. The average respondent is 50 years old.

Table 1.2: Summary statistics.

| Variable | Mean | Std. Dev. | Observations |
|---|---|---|---|
| *Disadvantageous income inequality* | | | |
| Occupation-age-gender | 0.468 | 0.377 | 79,384 |
| Occupation-age-cohabitation | 0.463 | 0.375 | 78,737 |
| Education-age-gender | 0.451 | 0.357 | 192,230 |
| Education-age-cohabitation | 0.445 | 0.352 | 191,430 |
| *Advantageous income inequality* | | | |
| Occupation-age-gender | 0.638 | 1.247 | 79,384 |
| Occupation-age-cohabitation | 0.632 | 1.235 | 78,737 |
| Education-age-gender | 0.616 | 1.23 | 192,230 |
| Education-age-cohabitation | 0.61 | 1.226 | 191,430 |
| Life satisfaction | 6.973 | 1.769 | 192,669 |
| Monthly income (TEUR) | 1.776 | 1.289 | 192,669 |
| Age | 50.224 | 17.039 | 192,669 |
| Education (years) | 12.303 | 2.69 | 192,669 |
| Children | 0.458 | 0.843 | 192,669 |
| Adults | 2.14 | 0.832 | 192,669 |
| Cohabitation | 0.716 | 0.451 | 192,669 |
| Interviews | 0.875 | 0.331 | 192,669 |
| Employed | 0.606 | 0.489 | 192,669 |
| Easterner | 0.262 | 0.44 | 192,669 |
| Male | 0.477 | 0.499 | 192,669 |
| Political conviction | 4.784 | 1.545 | 192,669 |

Reference groups by occupation include only individuals in full-time employment. Income and inequality measures in EUR 1,000. Satisfaction with life in general at the time of the survey for all individuals in the household 16 years of age and older. 0 means completely dissatisfied and 10 means completely satisfied. *Children* denotes no. of children living in the household. *Adults* denotes no. of adults in the household. *Interviews* is a binary variable equal one if the person was interviewed for the third time. *Political conviction* is self-rated political conviction on a scale from 0 (extreme left) to 10 (extreme right). Source: SOEP, v29.

[9]Only employed individuals are included in the reference group specification based on occupation. Furthermore, reference groups with fewer than 100 observations per year are dropped in the respective year, hence the discrepancy in the number of observations.

## 1.5 Results

A natural starting point to analyzing the relationship between peer income and happiness is to show that the comparison income effect persists even when endogenous and correlated effects are accounted for. To this end, I regress the average income of similar others not living in the same state (together with individual- and peer-demographic control variables and fixed effects) on self-reported happiness. The point estimates summarized in panel A of Table 1.3 indicate a negative and significant effect of average peer income on self-reported happiness for all four reference group specifications. This relationship is more pronounced when comparisons are assumed to take place among individuals with the same cohabitation status than the same gender. Restricting the sample to employed individuals, and defining reference groups according to occupation type instead of education affects the point estimates only slightly. These results are in line with most of the comparison income literature[10].

The performance of the parsimonious model can be compared to the rearranged F&S model by adding the average income distance to richer peers as a regressor. The simple model is preferable if the additional variable does not add information to predict self-reported life satisfaction. Panel B summarizes the point estimates of the extended model. For all reference group specifications, the coefficients of $D_{ipt}(x_t)$ are highly significant and negative. Moreover, the adjusted coefficients of determination are larger in the extended model. This implies that the F&S model has significantly better predictive power. The coefficients on peer income are significantly positive for all but the second reference group specification. In the extended model the coefficient on $\mu_i(x_{-it})$ represents the sign-reversed coefficient on advantageous inequality $\beta$. A positive significant coefficient on $\mu_i(x_{-it})$ therefore implies aversion to advantageous income inequality. Together with the negative coefficient on $D_{ipt}(x_t)$, the evidence from specifications (i), (iii), and (iv) suggests that the average survey participant has inequality averse preferences with $\alpha < \beta < 0$. Different to panel A, the coefficient on individual income in panel B is smaller and not significantly different from zero in all specifications. Although no causal relationship exists in either case, equation (1.2) states that the coefficient on income in the rearranged F&S model is increasing in $\beta$.

[10]Typically, individual and peer income is log-transformed to account for decreasing marginal utility. The linearity assumption does not qualitatively alter the results and is imposed in Table 1.3 to facilitate nested hypothesis testing.

Table 1.3: Comparison income effect and rearranged F&S model.

| Happiness (0-10) | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| | | *Panel A - Reduced model* | | |
| Income | 0.078*** | 0.077*** | 0.047*** | 0.046*** |
| | (0.013) | (0.013) | (0.011) | (0.011) |
| Comparison income | -0.147** | -0.228*** | -0.192*** | -0.227*** |
| | (0.066) | (0.079) | (0.069) | (0.070) |
| $\bar{R}^2$ | 0.013 | 0.013 | 0.013 | 0.012 |
| | | *Panel B - Extended model* | | |
| Income | 0.007 | 0.009 | -0.002 | -0.001 |
| | (0.009) | (0.009) | (0.003) | (0.003) |
| Comparison income | 0.203*** | 0.123 | 0.172** | 0.142** |
| | (0.074) | (0.085) | (0.072) | (0.072) |
| Disadvantageous inequality | -0.438*** | -0.418*** | -0.488*** | -0.477*** |
| | (0.037) | (0.037) | (0.026) | (0.026) |
| $\bar{R}^2$ | 0.016 | 0.016 | 0.016 | 0.015 |
| Control variables | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Reference group FE | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| State-year effects | Yes | Yes | Yes | Yes |
| Observations | 79,384 | 78,737 | 192,230 | 191,430 |
| Individuals | 18,831 | 18,806 | 34,380 | 34,264 |

OLS-regression. Standard Errors clustered by individual in parentheses. *Significant at 10%; **significant at 5%; *** significant at 1%. Inequality measures calculated w.r.t. Occupation-age-gender (i), Occupation-age-cohabitation (ii), Education-age-gender (iii), and Education-age-cohabitation (iv). Control variables: age, age$^2$, years of education, no. of children, no. of adults, cohabitation, no. of interviews, employment status, region of residence and reference group aggregates of the aforementioned. Source: SOEP v29.

The results from Table 1.3 support the predictive power of the F&S utility framework and suggest inequality averse preferences of the average individual for most specifications. It remains to be shown that these outcomes are not an artifact of the linearity assumptions imposed on the inequality measures, not driven by the assumption of interpersonal cardinal comparability of utility implied by ordinary least squares estimation, and robust for subsets of the population. The results from estimating the F&S model as outlined in equation (1.5) with three different weighting functions are summarized Table 1.4. Compared to the rearranged model, the effect of both inequality measures weakens when logarithmic income is used as a control variable. In line with the previous table, panel A suggests inequality averse preferences for the average person for all reference groups, albeit $\beta$ is considerably smaller in magnitude. The impact of changing the functional form of the inequality measures is exemplified in panel B and C. When small income differences receive a relatively larger weight, the relative size of $\alpha$ and $\beta$ changes. Upward looking preferences prevail when large income differences are assumed to be more relevant. However, relative to panel A and B, the adjusted coefficient of determination in panel C is smaller.

Table 1.4: Estimating interdependent preferences.

| Happiness (0-10) | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| | | *Panel A - Linear income differences* | | |
| ln(income) | 0.328*** | 0.299*** | 0.187*** | 0.194*** |
| | (0.053) | (0.057) | (0.040) | (0.039) |
| Advantageous inequality | -0.029*** | -0.028*** | -0.015*** | -0.016*** |
| | (0.009) | (0.009) | (0.005) | (0.005) |
| Disadvantageous inequality | -0.130** | -0.157*** | -0.251*** | -0.239*** |
| | (0.051) | (0.055) | (0.051) | (0.049) |
| | | *Panel B - Logarithmic income differences* | | |
| ln(income) | 0.328*** | 0.339*** | 0.302*** | 0.278*** |
| | (0.056) | (0.058) | (0.040) | (0.039) |
| Advantageous inequality† | -0.114*** | -0.090*** | -0.109*** | -0.106*** |
| | (0.019) | (0.019) | (0.016) | (0.015) |
| Disadvantageous inequality† | -0.094*** | -0.076*** | -0.096*** | -0.086*** |
| | (0.018) | (0.018) | (0.015) | (0.015) |
| | | *Panel C - Quadratic income differences* | | |
| ln(income) | 0.376*** | 0.361*** | 0.318*** | 0.313*** |
| | (0.026) | (0.026) | (0.017) | (0.017) |
| Advantageous inequality‡ | -0.191 | -0.729* | 0.005 | -0.252 |
| | (0.318) | (0.379) | (0.196) | (0.229) |
| Disadvantageous inequality‡ | -0.086*** | -0.082** | -0.010*** | -0.010*** |
| | (0.033) | (0.036) | (0.004) | (0.004) |
| Control variables | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Reference group FE | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| State-year effects | Yes | Yes | Yes | Yes |
| Observations | 79,384 | 78,737 | 192,230 | 191,430 |
| Individuals | 18,831 | 18,806 | 34,380 | 34,264 |

OLS-regression. Standard Errors clustered by individual in parentheses. *Significant at 10%; **significant at 5%; *** significant at 1%. Inequality measures calculated w.r.t. Occupation-age-gender (1), Occupation-age-cohabitation (2), Education-age-gender (3), and Education-age-cohabitation (4). †: The weighting functions $g_1^+(x_t)$ and $g_1^-(x_t)$ are applied to the inequality measures and assign weights decreasing in the income differences. ‡: The weighting functions $g_2^+(x_t)$ and $g_2^-(x_t)$ are applied to the inequality measures and assign weights increasing in the income differences. Control variables: age, age$^2$, years of education, no. of children, no. of adults, cohabitation, no. of interviews, employment status, region of residence and reference group aggregates of the aforementioned. Quadratic weighting function scaled by $10^6$. Source: SOEP v29.

Consider specification (i) of panel A in Table 1.4. Everything else being equal, a 100% raise in net real monthly income is associated with an increase in reported satisfaction by 0.33 points for the average individual or 19% of a standard-deviation of self-reported happiness. An increase in the average income distance to better-off others by EUR 1,000 decreases reported satisfaction by approximately 0.13 points or 7% of a standard-deviation. Keeping everything else equal, this suggests that an increase in monthly income of the average individual by 100% is predicted to not change perceived well-being, if at the same time the average distance to richer individuals increases by approximately EUR 2,500. The negative effect of advantageous income inequality is smaller. An increase in the average income distance to worse-off others by EUR 1,000 reduces satisfaction by approximately 0.03 points or 2% of a standard-deviation. A 100% increase in income does not change satisfaction, if at the same time the average distance to poorer individuals increases by approximately EUR 11.000. At best, these coefficients reflect the attitudes towards income inequality of the average native German in the period under consideration[11]. Experimental evidence suggests that there is considerable heterogeneity among attitudes towards payoff inequality. F&S propose a simple discrete distribution of $\alpha$ and $\beta$ consistent with the large experimental evidence on the ultimatum game. Their distributional assumptions imply population averages for $\alpha$ and $\beta$ of 0.5 and 0.3 respectively. Normalizing the coefficient on logarithmic income in specification (iii), the estimated population averages of $\alpha$ and $\beta$ are $0.4 \times 10^{-3}$ and $0.09 \times 10^{-3}$ respectively and thus of similar relative size but smaller in absolute magnitude.

By comparison, Cojocaru (2014) finds that a one standard-deviation increase in both advantageous and disadvantageous inequality is associated with a 1.9% reduction in the probability of reporting above-average life satisfaction. Considering the point estimates reported in column (i), a one standard-deviation change in inequality reduces self-reported life satisfaction by about 0.04 points or about 2% of a standard deviation. D'Ambrosio and Frick (2012) use annual instead of monthly income and include the levels instead of logarithms in the model. Their coefficient on disadvantageous inequality in absolute value is about four times as large as the coefficient they report for advantageous inequality. Different to my results, they find that life satisfaction is increasing in the income distance to poorer others.

Ordinary least squares estimation imposes the assumption that self-reported happiness measures are cardinally comparable between individuals. Although empirical evidence suggests that this assumption is fulfilled (Ferrer-i-Carbonell and Frijters,

[11]Non-reported estimations suggest that the coefficients remain stable when the sample period is extended to include years 1994-2012.

2004), latent variable models such as ordered probit with pseudo fixed effects and the BUC ordered logit estimator do not require this assumption and still account for unobserved heterogeneity. Estimates of the key parameters are reported in panel A and B of Table 1.5. Using ordered probit, the point estimates become more similar across reference groups. With BUC, inequality averse preferences prevail for specifications (ii)-(iv) only at 10% significance. As above, comparisons appear to be mostly upwards.

Table 1.5: Latent variable models and curvature.

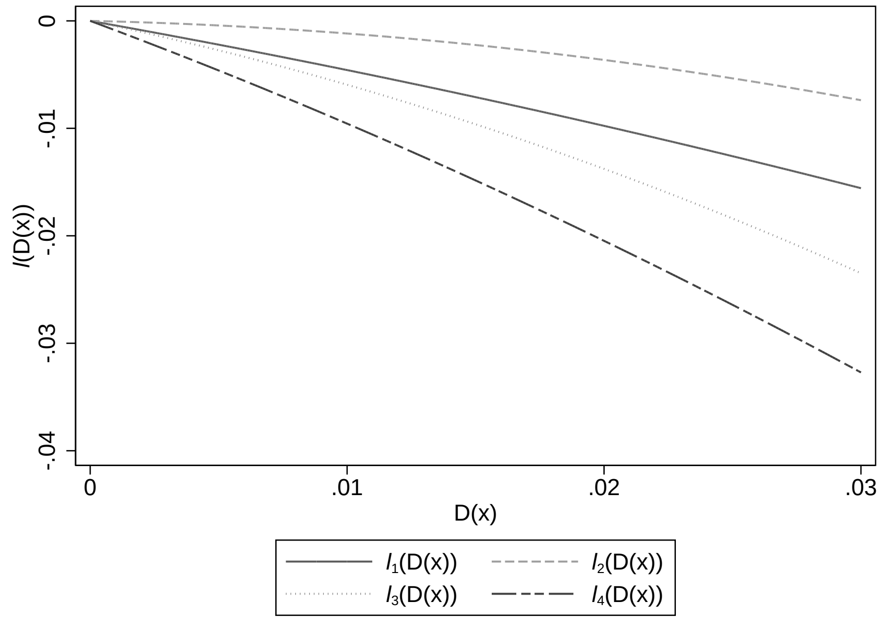
| Happiness (0-10) | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| | *Panel A - Ordered Probit†* | | | |
| Advantageous inequality | -0.021*** | -0.021*** | -0.016*** | -0.017*** |
| | (0.007) | (0.007) | (0.004) | (0.004) |
| Disadvantageous inequality | -0.133*** | -0.161*** | -0.181*** | -0.177*** |
| | (0.043) | (0.043) | (0.038) | (0.036) |
| | *Panel B - Blow-Up and Cluster* | | | |
| Advantageous inequality | -0.056*** | -0.036** | -0.020* | -0.020* |
| | (0.015) | (0.016) | (0.012) | (0.011) |
| Disadvantageous inequality | -0.052 | -0.321*** | -0.461*** | -0.474*** |
| | (0.080) | (0.101) | (0.090) | (0.079) |
| | *Panel C - Taylor Expansion‡* | | | |
| Advantageous inequality | -0.569*** | -0.475*** | -0.272*** | -0.292*** |
| | (0.161) | (0.168) | (0.085) | (0.085) |
| (Advantageous inequality)$^2$ | 0.087** | 0.065 | 0.016** | 0.018*** |
| | (0.042) | (0.043) | (0.006) | (0.006) |
| Disadvantageous inequality | -0.427 | -0.053 | -0.500 | -0.889 |
| | (0.883) | (0.917) | (0.799) | (0.770) |
| (Disadvantageous inequality)$^2$ | -3.065 | -6.434* | -9.423*** | -6.714** |
| | (3.713) | (3.666) | (3.448) | (3.314) |
| Control variables | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Reference group FE | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| State-year effects | Yes | Yes | Yes | Yes |
| Observations | 79,384 | 78,737 | 192,230 | 191,430 |
| Individuals | 18,831 | 18,806 | 34,380 | 34,264 |

OLS-regression. Standard Errors clustered by individual in parentheses. *Significant at 10%; **significant at 5%; *** significant at 1%. †: Individual FE are replaced with Mundlak (1978) pseudo FE. ‡: monthly income in 10,000 EUR used for computation. Inequality measures calculated w.r.t. Occupation-age-gender (i), Occupation-age-cohabitation (ii), Education-age-gender (iii), and Education-age-cohabitation (iv). Control variables: age, age$^2$, years of education, no. of children, no. of adults, cohabitation, no. of interviews, employment status, region of residence and reference group aggregates of the aforementioned. Source: SOEP v29.

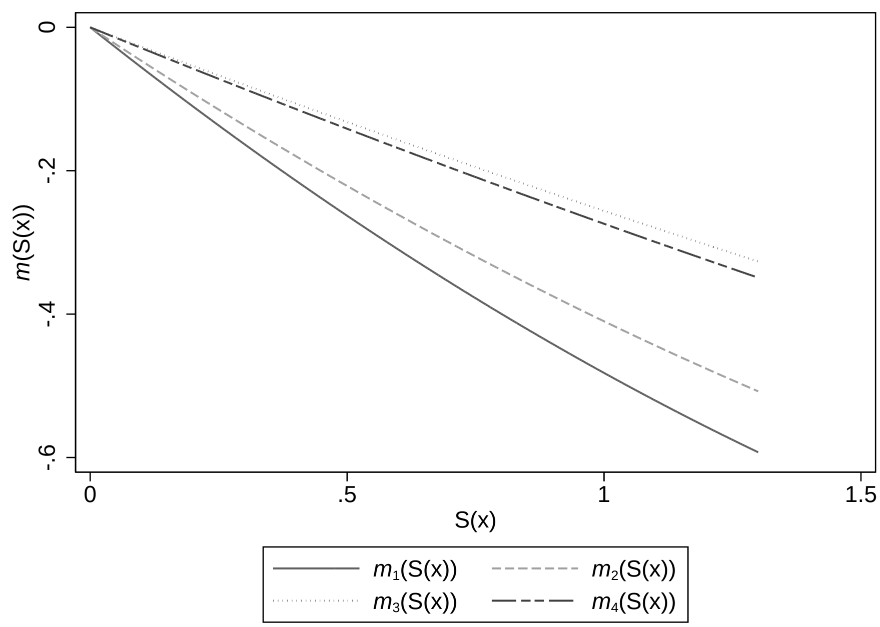
Convex preferences imply quasi-concavity of the utility function. To analyze the curvature of the utility framework with interdependent preferences, the linear-

Figure 1.1: Taylor approximation of D(x) and S(x) around sample averages (Income in EUR 10,000).

(a) Disadvantageous inequality




(b) Advantageous inequality



ity assumption can be replaced by additive separability such that $U_{ipt} = \zeta(z_{it}) + l(D_{ipt}(x_{pt})) + m(S_{ipt}(x_{pt}))$, where $z_{it}$ includes income. Assuming that utility is at least twice differentiable and continuous in the inequality measures, this allows to approximate the curvature by extending the baseline model to include the squares of $D$ and $S$. The results reported in panel C indicate that utility appears to be concave in $D$ and convex in $S$ around the sample average. Figure 1.1 visualizes this result. The relationship between advantageous income inequality and happiness appears to be well approximated by a function linear in the income differences as in panel A of Table 1.3.

A method to account for some of the heterogeneity in preferences is to estimate attitudes towards income inequality conditional on observable characteristics such as gender or age-cohort. Panel A of Table 1.6 shows the differences in attitudes towards inequality between men and women. While both genders across all specifications are on average negatively affected by advantageous income inequality, disadvantageous inequality affects men more strongly with reference groups by education. This is especially the case in specification (iii), which imposes the assumption that comparisons take place within gender. Panel B shows interactions of the inequality measures with indicator variables for young (younger than 35 years) and old (older than 46). Both relatively young and old individuals are on average more averse to advantageous income inequality than the comparison cohort. The effect of disadvantageous inequality however is not significantly different.

Alternatively, attitudes towards inequality can be estimated separately for East and West Germans or by political conviction. Panel A of Table 1.7 shows the differences in interdependent preferences between East and West Germans. In all specifications, the results predict that East Germans are on average more averse to (disadvantageous) income inequality than West Germans. This result implies that interdependent preferences are subject to societal influence and not inherent human characteristics. In 2005 and 2009 respondents to the SOEP questionnaire were asked to state their political conviction on a scale from 0 to 10. The former indicates that the individual identifies herself as a leftist and the latter that she identifies as a rightist. Assuming that political conviction is somewhat time invariant, I classify a respondent as a leftist if the average response from both years is three or lower. Likewise, an individual is classified as a rightist if the average response from both years is seven or higher, and a centrist otherwise[12]. Panel B summarizes the differential effect of political conviction on attitudes to income inequality. Both leftists and centrists are averse to income inequality. Although the point estimates are negative, there is no significant differential effect for leftists when the sample is restricted to employed individuals. Rightists on the other hand have upward looking preferences and are only affected by disadvantageous income inequality. In all specifications, the coefficients on advantageous inequality are jointly insignificant.

Table 1.6: Heterogeneity. Gender and Age.

| Happiness (0-10) | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| *Panel A - Gender* | | | | |
| Advantageous inequality | -0.046*** | -0.047*** | -0.015** | -0.016** |
| Disadvantageous inequality | -0.094 | -0.159** | -0.149** | -0.183*** |
| Advantageous inequality × Male | 0.024 | 0.030** | -0.003 | 0.001 |
| Disadvantageous inequality × Male | -0.043 | 0.013 | -0.168*** | -0.106** |
| *Panel B - Age* | | | | |
| Advantageous inequality × Young | -0.072** | -0.058** | -0.034* | -0.031* |
| Disadvantageous inequality × Young | -0.034 | 0.012 | 0.061 | 0.086 |
| Advantageous inequality | -0.005 | -0.009 | 0.005 | 0.006 |
| Disadvantageous inequality | -0.134* | -0.131* | -0.316*** | -0.285*** |
| Advantageous inequality × Old | -0.028* | -0.025* | -0.021* | -0.023* |
| Disadvantageous inequality × Old | 0.016 | -0.026 | 0.070 | 0.043 |
| Control variables | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Reference group FE | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| State-year effects | Yes | Yes | Yes | Yes |
| Observations | 79,384 | 78,737 | 192,230 | 191,430 |
| Individuals | 18,831 | 18,806 | 34,380 | 34,264 |

OLS-regression. Standard Errors clustered by individual in parentheses. *Significant at 10%; **significant at 5%; *** significant at 1%. Inequality measures calculated w.r.t. Occupation-age-gender (i), Occupation-age-cohabitation (ii), Education-age-gender (iii), and Education-age-cohabitation (iv). Control variables: age, age$^2$, years of education, no. of children, no. of adults, cohabitation, no. of interviews, employment status, region of residence and reference group aggregates of the aforementioned. Source: SOEP v29.

[12] Approximately 12% of the individuals in the sample are classified as rightists and 16% as leftists.

Table 1.7: Heterogeneity. Region and Political Conviction.

| Happiness (0-10) | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| | | *Panel A - Eastern Germany* | | |
| Advantageous inequality | -0.027*** | -0.025*** | -0.014*** | -0.015*** |
| Disadvantageous inequality | -0.078 | -0.104* | -0.160*** | -0.153*** |
| Advantageous inequality × East | -0.025 | -0.009 | -0.078*** | -0.067** |
| Disadvantageous inequality × East | -0.169*** | -0.166*** | -0.222*** | -0.201*** |
| | | *Panel B - Political Conviction* | | |
| Advantageous inequality × Leftist | -0.014 | -0.007 | -0.037** | -0.036** |
| Disadvantageous inequality × Leftist | -0.103 | -0.091 | -0.027 | -0.016 |
| Advantageous inequality | -0.034*** | -0.036*** | -0.016** | -0.018** |
| Disadvantageous inequality | -0.091* | -0.126** | -0.239*** | -0.235*** |
| Advantageous inequality × Rightist | 0.033* | 0.043** | 0.007 | 0.010 |
| Disadvantageous inequality × Rightist | -0.128* | -0.064 | -0.014 | 0.041 |
| Control variables | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Reference group FE | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| State-year effects | Yes | Yes | Yes | Yes |
| Observations | 79,384 | 78,737 | 192,230 | 191,430 |
| Individuals | 18,831 | 18,806 | 34,380 | 34,264 |

OLS-regression. Standard Errors clustered by individual in parentheses. *Significant at 10%; **significant at 5%; *** significant at 1%. Inequality measures calculated w.r.t. Occupation-age-gender (i), Occupation-age-cohabitation (ii), Education-age-gender (iii), and Education-age-cohabitation (iv). Control variables: age, age$^2$, years of education, no. of children, no. of adults, cohabitation, no. of interviews, employment status, region of residence and reference group aggregates of the aforementioned. Source: SOEP v29.

## 1.6 Discussion and conclusion

This paper introduces an empirical test for the predictive power of the comparison income model against a more general model of interdependent preferences. The results indicate that for all reference group specifications the F&S-type utility framework is better suited for predicting happiness scores than the simple comparison income model. The negative coefficient on average reference group income appears to be driven by aversion to income inequality rather than altruistic or spiteful preferences. The results are consistent across reference group specifications and for constant and logarithmic weighting functions. I focus on estimating the attitude towards income inequality of the average person and the relative predictive power of comparison income. It is likely that there exists strong heterogeneity among individuals when it comes to attitude towards inequality. A majority of individuals may be unaffected or even positively affected by income inequality. The results indicate significant gender difference in that men appear to be more strongly affected by disadvantageous income inequality. Also, relative to individuals between 35 and 45 years of age, both younger and older cohorts appear to be more affected by advantageous income inequality, presumably for different reasons. Individuals living in the states of the former GDR appear to be more averse to income inequality than those in West Germany, which confirms the strong effect of cultural background on norms, even more than twenty years after the German reunification. Consistent with this result, centrists and left-leaning individuals show inequality averse preferences. Right-leaning individuals on the other hand have upward looking preferences and are only affected by disadvantageous income inequality.

The comparisons are mostly upwards in that individuals are on average more affected by disadvantageous than advantageous income inequality. Normalizing the coefficient on income to one, the coefficients on both inequality measures with linear weighting functions are much smaller than predicted by game-theoretic experiments but the relative size is similar. The results do not appear to be an artifact of the imposed functional form of utility. F&S-type interdependent preferences impose strong assumptions on the utility function, and, when used with empirical data, on the perception of inequality in the society. If one is reluctant to attribute attitudes towards income inequality to the point estimates, the statistical significance of the average income distance to better-off others indicates a differential effect of comparison income on self-reported happiness. Nevertheless, the results suggest that F&S-type interdependent preferences account better for attitude of the average individual towards income of others than peer income alone.

Compared to Cojocaru (2014) and D'Ambrosio and Frick (2012) my results fall somewhat in the middle. Similar to Cojocaru (2014) I find on average inequality averse preferences. While his analysis using data from 27 transition economies suggests approximately the same effect size for advantageous and disadvantageous income inequality on individual happiness, my results using SOEP data indicate that aversion to advantageous income inequality is economically insignificant. D'Ambrosio and Frick (2012) on the other hand report spiteful instead of inequality averse preferences using an earlier version of the same data set. The authors neither define reference groups nor include time fixed effects in their model. Similar to my results, the effect of disadvantageous inequality affects happiness more strongly than the effect of advantageous inequality.

Despite the robustness across various alternative model specifications, sources of inconsistency remain. The defined reference groups might insufficiently approximate the income distribution relevant for individual comparison. Although the reflection problem may be mitigated by restricting reference groups to individuals from other states, including socio-demographic characteristics of peers, and reference group fixed effects, it is unknown to what extend exogenous and correlated effects still bias the results. Also, it is unknown to which degree individuals perceive their own relative position in the reference group income distribution. Experimental evidence suggests that there is considerable heterogeneity in the population regarding interdependent preferences. This study confirms that the estimated coefficients for the average individual are relatively stable for subsamples by gender, residency in the states of the former GDR, and age-cohort. In future research, random coefficient models could be employed to estimate the distribution of $\alpha$ and $\beta$ in the population.

The analysis in this chapter shows that, ceteris paribus, self-reported happiness decreases in disadvantageous, and, to a lesser extent, advantageous income inequality when reference groups are defined by demographic characteristics. Most economists agree that due to the effect on incentives, neither the absence nor extreme levels of income inequality maximize economic growth. A social planner whose objective is to maximize aggregate life satisfaction might be tempted to reduce income inequality either for the entire society or within professions. While such policies may cause individuals with relatively low income to evaluate their lifetime achievements and social status more positively, reduced incentives for high income earners may create more harm than good for the economy overall. Given the interdependencies between income inequality and economic growth, and the contributions of the latter to job security, income growth, and social cohesion – all determinants of life satisfaction, it is questionable whether income inequality can be reduced while holding economic growth constant.

# Bibliography

**Baetschmann, Gregori, Kevin E. Staub, and Rainer Winkelmann**, "Consistent estimation of the fixed effects ordered logit model," *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 2015, *178* (3), 685–703.

**Chamberlain, Gary**, "Analysis of Covariance with Qualitative Data," *The Review of Economic Studies*, 1980, *47* (1), 225–238.

**Clark, Andrew E. and Andrew J. Oswald**, "Unhappiness and Unemployment," *The Economic Journal*, 1994, *104* (424), 648–659.

**Clark, Andrew E and Claudia Senik**, "Who compares to whom? the anatomy of income comparisons in europe," *The Economic Journal*, 2010, *120* (544), 573–594.

**Clark, Andrew E., Paul Frijters, and Michael A. Shields**, "Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles," *Journal of Economic Literature*, March 2008, *46* (1), 95–144.

**Cojocaru, Alexandru**, "Fairness and inequality tolerance: Evidence from the Life in Transition Survey," *Journal of Comparative Economics*, 2014, *42* (3), 590 – 608.

**D'Ambrosio, Conchita and Joachim R Frick**, "Individual wellbeing in a dynamic perspective," *Economica*, 2012, *79* (314), 284–302.

**Deaton, Angus**, "Health, Inequality, and Economic Development," *Journal of Economic Literature*, 2003, *41* (1), 113–158.

**Drechsel-Grau, Moritz and Kai D. Schmid**, "Consumption–savings decisions under upward-looking comparisons," *Journal of Economic Behavior & Organization*, 2014, *106*, 254 – 268.

**Duesenberry, James H.**, *Income, Saving and the Theory of Consumer Behavior*, Harvard University Press Cambridge, 1949.

**Fehr, Ernst and Klaus M Schmidt**, "A theory of fairness, competition, and cooperation," *The Quarterly Journal of Economics*, 1999, *114* (3), 817–868.

**Ferrer-i-Carbonell, Ada**, "Income and well-being: an empirical analysis of the comparison income effect," *Journal of Public Economics*, 2005, *89* (5), 997–1019.

_ **and Paul Frijters**, "How Important is Methodology for the estimates of the determinants of Happiness?," *The Economic Journal*, 2004, *114* (497), 641–659.

**Hirschman, Albert O**, "The changing tolerance for income inequality in the course of economic development," *World Development*, 1973, pp. 544–566.

**Hopkins, Ed**, "Inequality, happiness and relative concerns: What actually is their relationship?," *The Journal of Economic Inequality*, Dec 2008, *6* (4), 351–372.

_ **and Tatiana Kornienko**, "Running to keep in the same place: Consumer choice as a game of status," *American Economic Review*, 2004, pp. 1085–1107.

**Landua, Detlef**, "An attempt to classify satisfaction changes: Methodological and content aspects of a longitudinal problem," *Social Indicators Research*, 1992, *26* (3), 221–241.

**Luttmer, Erzo F. P.**, "Neighbors as Negatives: Relative Earnings and Well-Being," *The Quarterly Journal of Economics*, 2005, *120* (3), 963–1002.

**Manski, Charles F.**, "Identification of Endogenous Social Effects: The Reflection Problem," *The Review of Economic Studies*, 1993, *60* (3), 531–542.

_ , *Identification Problems in the Social Sciences*, Harvard University Press, 1995.

**Maurer, Jürgen and André Meier**, "Smooth it Like the 'Joneses'? Estimating Peer-Group Effects in Intertemporal Consumption Choice*," *The Economic Journal*, 2008, *118* (527), 454–476.

**McBride, Michael**, "Relative-income effects on subjective well-being in the cross-section," *Journal of Economic Behavior & Organization*, July 2001, *45* (3), 251–278.

**Mundlak, Yair**, "On the Pooling of Time Series and Cross Section Data," *Econometrica*, 1978, *46* (1), 69–85.

**Senik, Claudia**, "When information dominates comparison: Learning from Russian subjective panel data," *Journal of Public Economics*, 2004, *88* (9), 2099 – 2123.

**van de Stadt, Huib, Arie Kapteyn, and Sara van de Geer**, "The Relativity of Utility: Evidence from Panel Data," *The Review of Economics and Statistics*, May 1985, *67* (2), 179–187.

# Chapter 2

# Rural Banks and Agricultural Production: Evidence from India's Social Banking Experiment

## 2.1 Introduction

Improving access to formal banking and financial services has long been seen as a key tool to reducing poverty in developing countries (Aghion and Bolton, 1997; Banerjee and Newman, 1993). Indeed, recent empirical research has shown its effectiveness in this regard, including in India (Burgess and Pande, 2005; Fulford, 2013; Kochar, 2011). Despite this, we know relatively little about the underlying pathways through which access to banks can lead to reductions in poverty. In this study, we use district-level panel data to study India's government-led rural banking program in the 1980s to shed light on these potential pathways, focusing on agricultural production.

Access to banking services has the potential to increase agricultural productivity, and thereby rural incomes, via three leading pathways. First, such services may help individual farmers to overcome liquidity constraints, which can cause under-usage of inputs. We investigate this by analyzing the impact of bank growth on agricultural yields, as well as the use of inputs including land, irrigation, seeds, fertilizers and machinery. Second, bank credit can help improve intertemporal consumption smoothing, and therefore increase farmers' willingness to engage in riskier but more profitable activities. We assess this potential channel by considering changes in crop portfolio over time in response to bank growth, specifically shifts towards more volatile but higher return crops. Third, banks can provide some insurance against adverse weather shocks. To test for this, we examine whether banks attenuate the relationship between lagged rainfall and contemporaneous production.

Our results show that improved access to banks did significantly increase agricultural yields and production. Specifically, a 1% growth in banks is associated with a 0.4% growth in yields. To decompose this relationship further, we document an increase in the use of relatively more expensive but higher-yielding variety (HYV) seeds for cereal cultivation. Moreover, bank growth appears to shift the overall portfolio towards more cash crops and double-cropping during the winter season. Finally, we find banks had an attenuating influence on the negative effects of lagged rainfall shocks through changes in the use of irrigation resources.

Evaluating the causal impacts of formal banking services on agricultural production in a non-experimental setting is challenging. For instance, banks may choose to open new branches in the most productive regions at baseline, but lower growth potential, leading OLS to underestimate the true effects. In contrast, banks may choose to open new branches in regions with lower baseline productivity, but higher growth potential, leading OLS to overestimate the true effects. In order to address these potential biases, we exploit a series of central-government regulations, aimed explicitly at expanding the rural banking infrastructure in India during the 1980s, to generate a time-varying instrument for bank growth at the district level.

From 1978 to 1990, three consecutive periods of Branch Licensing Policies (BLPs) guided the spread of banking infrastructure in India. Instigated to ensure a more equitable distribution of banking facilities across the country, the BLPs regulated the location of new branches towards unbanked regions. Using a target population-per-branch ratio (set to the national average at the onset of each period), a district was identified as deficit if found to be above the stipulated threshold. If classified as such, the district was assigned a detailed branch expansion program. Compliance was monitored at the end of each period, when districts were reclassified based on their updated population-per-branch ratio.

Our identification strategy leverages the fact that the same district can be deficit in one period, and not so in another. Such policy-induced changes in bank growth within a district over time allows us to estimate more accurately the causal impacts of this major expansion in banking infrastructure in 20$^{\text{th}}$ century India. To test the validity of this empirical strategy more formally, we carry out a number of placebo tests that show the instrument to be uncorrelated with potentially confounding factors such as growths in physical infrastructure (namely road networks), market development, other government policies such as preferential lending to agriculture. Furthermore, we show that the instrument is uncorrelated with pre-trends in our outcomes.

Our unit of analysis is a district-BLP period, the same as that used to plan and implement the rural banking program. Spanning the decade covered under the three BLP periods, 1978-1988, our panel includes a total of 218 districts across 15 states. We digitize the number of rural banks for each district-year, using the Reserve Bank of India's (RBI) Basic Statistical Reports (BSRs). Data on agricultural inputs and production indicators over the same period are obtained from the Village Dynamics in South Asia Macro-Meso Database (VDSA).

This study is related to several strands of literature. First, a number of papers have documented the poverty-reducing effects of India's social banking program (Burgess and Pande, 2005; Fulford, 2013; Kochar, 2011). Specifically, Burgess and Pande (2005) report that the growth in banking infrastructure can account for up to 15% of the reduction in the head count ratio during the 1970s and 80s. Our study adds to this literature by identifying the underlying pathways for the effect on poverty, examining responses in a detailed set of agricultural production choices to bank branch growth.

While the policy evaluated in this chapter is specific to India and dates back to the 1980s, the fundamental question of assessing the impact from access to banking services has received renewed attention recently (Demirgüç-Kunt et al., 2015). Experimental evidence testing the impact of expanding access to basic bank accounts across three countries by Dupas et al. (2018) find large effects on savings rate among users. However, the authors do not detect any sizable intention-to-treat effects on the study population, suggesting that access alone may not lead to notable improvements on average.

Our study also contributes to the literature on agricultural technology adoption. Previous research has examined numerous barriers, including lack of learning (Conley and Udry, 2010; Hanna et al., 2014), access to markets (Ashraf et al., 2009), high transaction costs (Suri, 2011), time-inconsistent preferences (Duflo et al., 2011), as well as liquidity constraints (Beaman et al., 2014; Karlan et al., 2014). Much of the recent work has come from randomized control trials. This chapter provides complementary insight by examining in detail the impacts of a major policy-led expansion in rural banking infrastructure from a highly important developing country.

The rest of the chapter is structured as follows. Section 2.2 presents a historical overview of formal banking in India. Section 2.3 describes the data and Section 2.4 the empirical strategy. Section 2.5 reports results on agricultural output, inputs, and crop choice, as well as the interacting effect of bank growth with lagged rainfall. Section 2.6 concludes.

## 2.2 Social Banking in India

Despite some initial regulation by the Reserve Bank of India (RBI) encouraging the spread of banking infrastructure by commercial banks during the early 1960s, the foundation stone for a nationwide social banking program occurred in 1969 with the government seizing 'social control' of 14 commercial banks (Panagariya 2006). A second nationalization phase in 1980 of an additional 6 banks, brought approximately 91% of banking business in India under central governance. The Preamble to the Banking Companies Act of 1980 transferring the undertaking of these 6 private banks clearly sets the intention of the Government at the time:

> *"An Act to provide for the acquisition and transfer of the undertakings, in order further to control the heights of the economy, to meet progressively, and serve better, the needs of the development of the economy and to promote the welfare of the people, in conformity with the policy of the State."*

The following decade (1980-1990) witnessed the amplification of financial services at the core of the central government anti-poverty campaign via three leading policies: bank branch licensing, priority sector lending, and subsidized credit.

Branch Licensing Policies (BLPs) were instigated to ensure an equitable distribution of banking facilities across the country[1]. The 1980s witnessed three consecutive BLP periods, which saw the national number of rural bank branches increase by

[1]BLPs were first introduced in 1962, stipulating that commercial banks should open branches in a ratio of 1:2 between banked and unbanked locations. This ratio later changed to 1:1 in 1968. In 1977, the 'entitlement formula' was introduced which required banks to open a minimum of four branches in rural and semi-urban locations for every branch opened in an urban center. This ratio applied only to banks with less than 60% of their offices in rural and semi-urban areas. Banks satisfying the threshold only had to abide to a ratio of 1:2 new bank branches in urban and rural areas respectively.

approximately 15,000 (see panel A of Figure 2.1). The policies employed a target population to bank branch ratio in order to identify districts as deficit in finance. The first BLP period (BLP-1; 1979-1982) was implemented on a target of 20,000 people per rural bank branch, which was revised down to 17,000 for the second (BLP-2; 1982-1985) and third (BLP-3; 1985-1990)[2] BLP periods[3]. The ratio, stipulated based on the national average at the onset of the period, was calculated on the basis of the 1981 India census population in all cases and the updated number of banks at the onset of the specific BLP period. Districts whose existing number of rural banks generated a ratio above the specified threshold were classified as deficit and consequently assigned to a detailed branch expansion program by the RBI. Compliance to the policy guidelines was monitored at the end of each BLP period by State governments. Districts were reclassified according to their updated information. We exploit this reclassification in deficit status to generate a time-varying instrument for bank growth at the district level.

Alongside improved access to banking services, the 1980s witnessed a surge in the amount of finance disbursed to farmers. As shown in panel B of Figure 2.1, the average loan size per farm rose from approximately 700 Rupees in 1978 to over 2,000 Rupees by 1990. This period of change within the rural banking sector, appears to be matched by considerable improvements in the agricultural sector. As can be observed in panel A of Figure 2.2, total annual production increased by over 200 billion Rupees from 1978 to 1990. This rise in output does not appear to be driven by increased land area allocated to agricultural use, but rather a shift towards intensification of practices by adopting high-yielding varieties (see panel B of Figure 2.2). As a preview to our results, bank branch growth appears to have significantly relaxed some of the liquidity constraints faced by farmers and encouraged adoption of new inputs such as improved seeds. However, the extent of financial services received is unlikely to have been consequential enough for larger investments such as machinery (as a note

[2]In 1989, the emphasis started to shift from overt expansion to ensuring the viability of bank business in remote rural areas. A Service Area Approach (SAA) was therefore introduced to the BLP regulations of that period, such that a block of 15 to 25 villages were assigned to a specific bank. According to this new rule, branch construction was to be guided by both a target ratio of villages per bank in addition to the target population per bank ratio. Since we do not have access to village level data required to identify the rules guiding the implementation of this SAA, we limit our analysis to the BLP guidelines preceding this amendment.

[3]A timeline of these changes to the BLPs is summarized in Table B.1. Specific details on the implementation of the BLPs are reported in the RBI, Report on Currency and Finance annual volumes of that period.

of comparison; the cost of a tractor would have been approximately 10 times an average farm loan).

During the decade of the 1980s, the central government also significantly reinforced its priority sector lending initiative aimed at invigorating growth among the weaker sectors of the economy[4]. Agriculture, given its high poverty burden as well as its vital role in achieving self-sufficiency of food production, was considered a key sector eligible for this directed finance. District level targets were calculated as a measure of Direct Finance to Agriculture (DFA) as a proportion of total outstanding credit. Specifically, regulatory guidelines in 1983 stipulated a ratio of 15% to be achieved by 1985, which was revised upwards to 16% by 1987 and finally 18% by 1990[5]. Compliance was monitored on an annual basis by the District Level Task Force using data from the previous financial year. Districts falling short of the threshold were assigned to credit expansion programs in order to achieve the required targets. Given the close link between the BLPs and the priority sector lending initiative, we verify that our instruments guiding bank branch growth were indeed independent from the district level DFA targets. Our results suggest that the deficit status in access to banking services did not affect a districts' proportional lending to the agricultural sector.

Also, pursued during this decade was the Integrated Rural Development Programme (IRDP), India's largest poverty alleviation campaign at the time. The primary channel for this initiative was targeted subsidized credit intended to increase productive assets and encourage self-employment among small and marginal farmers, agricultural laborers, and rural artisans. The overarching objective of this program was to raise an average of 3,000 below-poverty-line households per administrative block above this threshold. Launched in 1978, the program initially provided the same level of financial assistance to each block in order to meet the requirements of the policy. However, in 1985, the rules guiding the IRDP expenditures changed such that for the following two years (1985-87) 50% of the allocation received was determined on the basis of poverty incidence within the block. This was further revised 1987, such that allocation of expenditure thereafter was based entirely on the level

[4]During the previous decade, regulatory targets had already been introduced compelling banks to extend at least one third of their outstanding credit to agriculture, small-scale industries, and small borrowers by 1979.

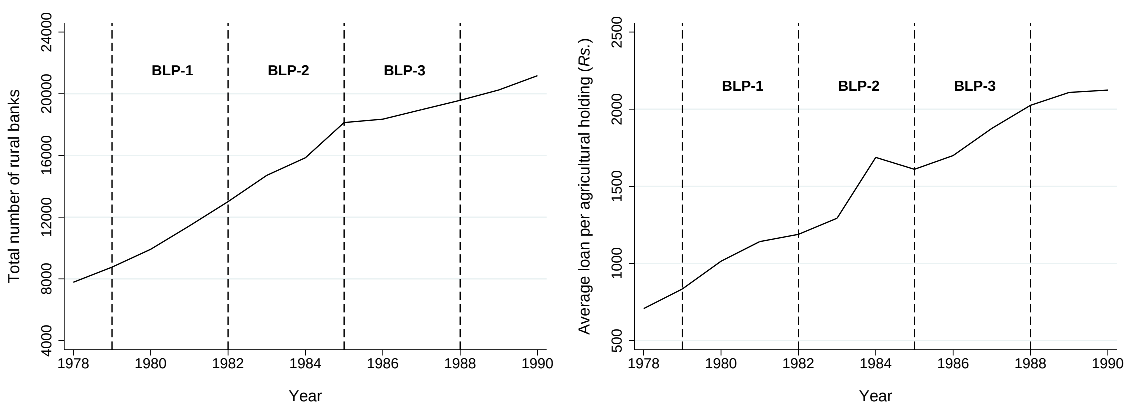
[5]A timeline of these changes to the DFA policies is summarized in Table B.1. Regulations related to this policy can be found in detail within the RBI, Report on Currency and Finance annual volumes of that period.

of poverty[6]. We may expect that additional financial assistance provided under the IRDP post 1985 may confound with the BLPs if districts which were classified as deficit in access to banking services were also poorer. As such, we review our main results when limiting the sample to the two BLP periods prior to 1985 (BLP-1 and BLP-2) during which the IRDP provided equal assistance across the country. This robustness test confirms that our results are consistent to this limited time period, and hence not confounded to the IRDP implementation strategy post 1985.

Following a decade of intensive public sector involvement in poverty alleviation programs by leveraging rural financial markets, India suffered a severe imbalance of payments. This forced the central government to largely abandon its social banking experiment at the dawn of the 1990s. The following decades witnessed instead a shift towards liberalization of the banking sector and the consolidation of its existing infrastructure.

Figure 2.1: Rural finance (1978-1990).

(a) Panel A: Rural banks (b) Panel B: Direct finance to agriculture



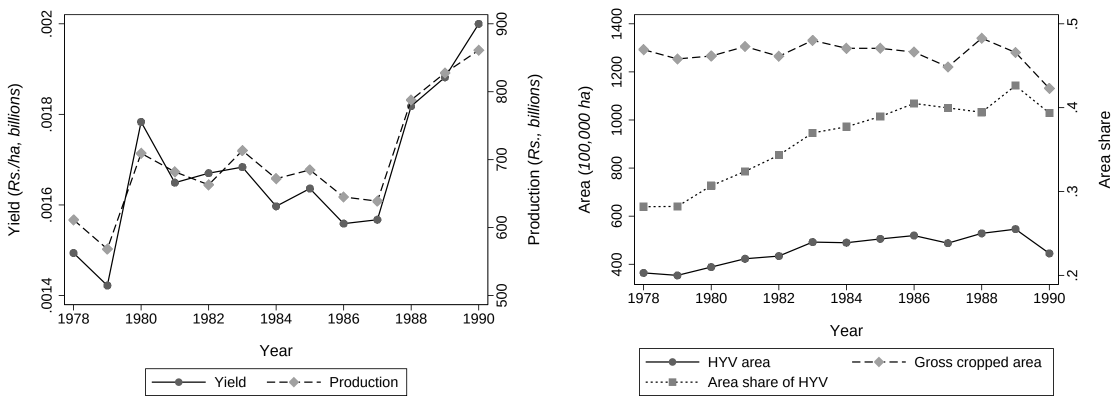

Notes: District-wise data on the number of rural banks and average loan per agricultural holding, aggregated to the country level for each year from 1978 to 1990. Loan per agricultural holding is calculated as the total direct finance to agriculture divided by the total number of land holdings. Direct finance to agriculture, reported in Rupees, is deflated using all-India CPI with 1990 base year. Sample of 218 districts.

[6]A timeline of these changes to the IRDP is summarized in Table B.1. Details of this program can be found in documents from the Planning Commission of 1980.

Figure 2.2: Agricultural production and cropped area (1978-1990).

(a) Panel A: Output

(b) Panel B: Area




Notes: District-wise data on yield, production, and land area, aggregated to the country level for each year from 1978 to 1990. Yield and production measures are deflated using all-India CPI with 1990 base year. Sample of 218 districts.

## 2.3 Data

For the purpose of this study, we have assembled a detailed dataset on agricultural production and finance over a ten year period from 1979 to 1988. This enables us to capture the three BLP periods guiding rural bank branch expansion during the 1980s[7]. Our unit of analysis is at the district-BLP level. Districts form the administrative unit immediately below that of the Indian state. Importantly for our identification, districts were also the platform used by the BLP regulations to implement improved access to banking services across the country.

Our banking indicator –number of rural bank branches– was digitized from the Basic Statistical Reports (BSR) available from the RBIs banking archives. These reports include district wise information on the number of bank branch offices in rural, semi-urban, and urban areas. Data on district rural population was obtained from the 1981 India Population Census. By calculating the ratio of rural population per bank branch, we recreate the exact criteria by which districts were classified as deficit in finance (see Table B.2 for details on the construction of the financial indicators). As reported in panel A of Table 2.1, at the onset of the policy in 1979,

[7]In 1989, BLP-3 was amended to include a Service Area Approach. Under the SSA, a target ratio of villages per bank was stipulated. Due to the lack of village level data, we cannot identify the exact regulations guiding bank growth in this period. As such, we limit our analysis to the years preceding this amendment.

91.6% of districts were classified as deficit with an average bank serving approximately 52,000 people. A decade later, following the three BLP periods we study, the share of deficit districts had fallen to 37% and the policy target of 17,000 people per bank branch had been achieved.

We draw upon the Village Dynamics in South Asia Macro-Meso Database (VDSA) for all data on agricultural indicators. Compiled by the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) from various official government data sources, the database covers all districts for 19 Indian states from 1966 to 2009 (using 1966 district boundaries so as to maintain consistency over time). For the purpose of this study, we assembled data on key agricultural inputs including land, irrigation, seeds, fertilizer, and machinery (see Table B.2 for details on the construction of the agricultural indicators). Additionally, we calculated an aggregate measure of agricultural production and yield using output and farmer harvest prices[8] for 15 major crops[9]. As in the case of finance, agriculture appears to have witnessed a significant shift during the 1980s. Average yield increased substantially by over 1,000 Rupees per hectare from 1978 to 1988, alongside a consistent rise in all inputs over time (see panel B of Table 2.1).

Weather data, which we use to test the relationship between access to finance and exogenous rainfall shocks, is jointly produced by the National Center for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR) since 1948 (for information and link to the database, see Kistler et al. (2001))[10]. The data is extracted from gridded daily datasets, assembled from non-public weather station information and sophisticated climate models to construct daily precipitation records for $1°$ (latitude) $\times$ $1°$ (longitude) grid points (excluding ocean sites). We match these grid points to each of the districts in our sample by taking weighted averages of the total precipitation variables for all grid points overlapping the district (the weights used are based on the area of each grid point

[8] These are the producer prices which farmers receive. Due to missing data for prices at the district level, we estimate prices at the country level for the purpose of our analysis. All prices are deflated using an all-India CPI with 1990 as the base year.

[9] The 15 crops are: barley, chickpea, cotton, finger millet, groundnut, linseed, maize, pearl millet, pigeon pea, rice, rape and mustard seed, sesame, sorghum, sugarcane, and wheat. These 15 crops account for approximately 74% of total gross cropped area across districts and years.

[10] The advantage of this data, assembled under the "Reanalysis" project, is that it produces a retroactive record of global analyses of atmospheric fields using a constant data assimilation system. This limits errors, such as perceived jumps in climate outcomes, associated with changes in the operational (real-time) data assimilation methods.

coinciding with the district). Over the period of our study, India witnessed a series of widespread droughts. This is reflected in panel C of Table 2.1 which shows a negative deviation from the long term mean in rainfall[11], of -6.1% and -5.8% for the years 1982 and 1985 respectively.

The complete dataset covers 321 districts, across 15 States of India[12]. We use information on changes in district boundaries across census years, presented by Kumar and Somanathan (2009), to bring the banking dataset to 1971 district borders. This ensures consistency in boundaries between our two data sources. However, as the BLPs were planned and implemented on 1981 borders, we focus our analysis on those districts which did not experience any border changes from 1971-1991. This reduces our sample to 237 districts; 74% of our original dataset. Additionally, we limit our sample to those districts which have non-missing information on all indicators for all 10 years of data. As a result, we loose an additional 19 districts. This selection leaves us with a final sample of 218 districts which form the basis for all of our analysis reported in this study.

### 2.3.1 Measuring crop choice

In this study, we measure change in the share of GCA grown with crops identified as having the following characteristics – high volatility, water sensitive, grown in winter, and cash based.

With respect to high volatility, we are interested in capturing crops which produce above average under favorable circumstances, but also suffer above average losses when kept under resource stress. While some studies on yield volatility of individual crops exist (Muchow, 1989; Singh and Singh, 1995; Rurinda et al., 2014), the results from these are not comparable as they impose different levels of stress. We therefore calculate our own measure of volatility. Using data from 1968 to 2000, we compute the coefficient of variation (CV) in yield for each crop grown at the State level. The subset of crops with above average relative yield volatility are categorized as high–volatility. We then calculate the area share (of GCA), at the State level, grown with these crops. This indicator forms our measure of risky but profitable crop choice[13].

[11] Long term mean is calculated as the average annual rainfall in a district over a 60 year period, from 1948-2008.

[12] In 1971 India had a total of 18 States. Covering over 95% of the total population, our sample of 15 States includes: Andhra Pradesh, Bihar, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal.

[13] The CV allows for comparisons between crops and is therefore preferable to other measures of

Table 2.1: Descriptive statistics.

| | 1979 | 1982 | 1985 | 1988 |
|---|---|---|---|---|
| | Mean (sd) (1) | Mean (sd) (2) | Mean (sd) (3) | Mean (sd) (4) |
| Panel A: Finance | | | | |
| Rural bank branches (*Nb.*) | 40.7570 | 60.205 | 83.662 | 89.070 |
| | (27.331) | (30.458) | (35.082) | (36.277) |
| Population to bank branch ratio (‘000 *pp*) | 52.113 | 26.363 | 18.054 | 16.234 |
| | (25.872) | (9.253) | (5.548) | (5.188) |
| Share of deficit district (%) | 0.916 | 0.860 | 0.556 | 0.373 |
| | (0.278) | (0.347) | (0.498) | (0.485) |
| Panel B: Agriculture | | | | |
| Output: | | | | |
| Yield (‘00 *Rs./ha*) | 44.641 | 52.788 | 51.549 | 57.276 |
| | (28.711) | (29.716) | (30.101) | (30.353) |
| Production (*Bn Rs.*) | 1.760 | 2.080 | 2.086 | 2.465 |
| | (1.353) | (1.458) | (1.574) | (1.730) |
| Inputs: | | | | |
| Gross cropped area (‘000 *ha*) | 415.448 | 422.723 | 431.078 | 454.942 |
| | (208.155) | (212.840) | (212.838) | (225.795) |
| Gross irrigated area (‘000 *ha*) | 142.231 | 157.725 | 159.055 | 185.739 |
| | (136.327) | (146.927) | (149.604) | (159.239) |
| Share of HYV (%) | 0.271 | 0.333 | 0.360 | 0.413 |
| | (0.183) | (0.190) | (0.197) | (0.212) |
| Nitrogen fertilizer (*tons/ha*) | 0.027 | 0.035 | 0.037 | 0.065 |
| | (0.026) | (0.035) | (0.037) | (0.151) |
| Potassium fertilizer (*tons/ha*) | 0.006 | 0.007 | 0.007 | 0.017 |
| | (0.011) | (0.011) | (0.014) | (0.114) |
| Phosphorus fertilizer (*tons/ha*) | 0.010 | 0.013 | 0.014 | 0.026 |
| | (0.011) | (0.013) | (0.015) | (0.046) |
| Pumps (‘000 *Nb.*)[a] | 15.598 | 20.685 | 28.512 | |
| | (25.947) | (25.450) | (29.535) | |
| Tractors (‘000 *Nb.*)[a] | 0.768 | 1.277 | 2.214 | |
| | (1.305) | (1.754) | (2.657) | |
| Panel C: Weather | | | | |
| Annual rainfall (*mm*) | 967.872 | 916.121 | 931.033 | 916.533 |
| | (392.872) | (374.042) | (430.781) | (343.687) |
| Deviation in long-term rainfall (%) | -1.552 | -6.136 | -5.896 | 0.993 |
| | (16.295) | (12.682) | (10.921) | (16.122) |
| Districts | 214 | 215 | 216 | 201 |

Notes: For a description of each variable source and construction, refer to Table B.2. Sample of 218 districts. Variation in observations are due to missing data on any one of the variables at the district level for that particular year. [a]Column (1) is calculated based on 1977 data, and Column (3) using 1987 data.

Of the 15 major crops, on average 11 varieties are planted in each sample State

dispersion such as the standard deviation. Furthermore, the volatility of a crop depends predominantly on climatic factors. Therefore, the same crop may show low yield variation in one State and high variation in another. Using the CV allows for relative categorization, circumventing problems arising when classifying each crop independently instead of relative to others in the same State.

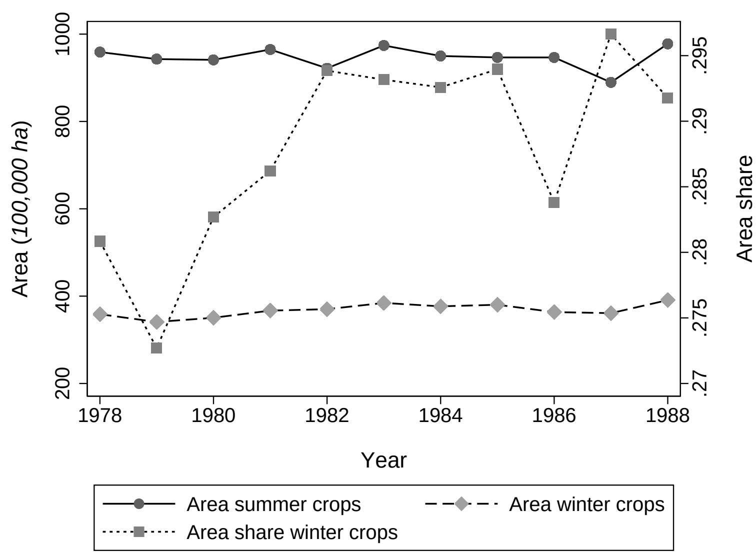
and approximately five of these show above average yield volatility. Cotton, sesame, rapeseed and mustard show particularly high yield volatility in most States.

During the 1980s, the lion's share of farming in India was rain-fed. Rainfall was therefore a crucial source of yield volatility. However, while some crops naturally respond more strongly to water than others, they may not necessarily be more dependent on rainfall if they are largely irrigated. To determine crops most susceptible to rainfall, we compute a regression of annual rainfall on crop yield; using district wise data pooled at the State level from 1968 to 2000. For each State, the absolute values of the t-statistics obtained from these regressions are ranked. In a given State, the subset of crops for which the effect of rainfall on yield is larger than average are categorized as rain–sensitive. Across all years, about 38% of the GCA is allocated to rain–sensitive crops. Rice, sorghum, and groundnut respond strongly to rainfall in most States. The yields of sugarcane, rapeseed, and mustard on the other hand, show the weakest correlation with annual rainfall.

Most crops are planted in the summer Kharif season (July to October), as this period receives the monsoon rainfall. However, some crops such as barley and wheat are planted during the winter Rabi season (October to March)[14]. Winter grown crops are often considered more risky and resource intensive, as they rely on artificial irrigation. As shown in Figure 2.3, the area dedicated to summer crops is more than three times as large as the area dedicated to winter crops. Over the study period, we find that while the aggregate area sown with summer and winter crops remains approximately stable, the area share of winter crops increases by approximately 7.5% between 1979 to 1988. As our final indicator of crop choice, we measure the share of GCA grown with cash crops. These crops cannot be used for household consumption, as they require post-harvest processing. They are however, generally considered to be more profitable. Cotton, sugarcane, and oilseeds (including linseed, soya, groundnut, rapeseed and mustard) are all considered cash crops.

[14]Among the 15 crops for which we have yield data, barley, chickpea, linseed, mustard, rapeseed, sesame, soya, and wheat are all winter crops.

Figure 2.3: Area allocated to summer and winter crops.




Notes: District-wise data on land area allocated to summer and winter crops, aggregated to the country level for each year from 1978 to 1988. Summer crops include: cotton, finger millet, groundnut, maize, pearl millet, pigeon pea, rice, sorghum, and sugarcane .Winter crops include: barley, chickpea, linseed, mustard, rapeseed, sesame, soya, and wheat. Sample of 218 districts.

## 2.4 Empirical Strategy

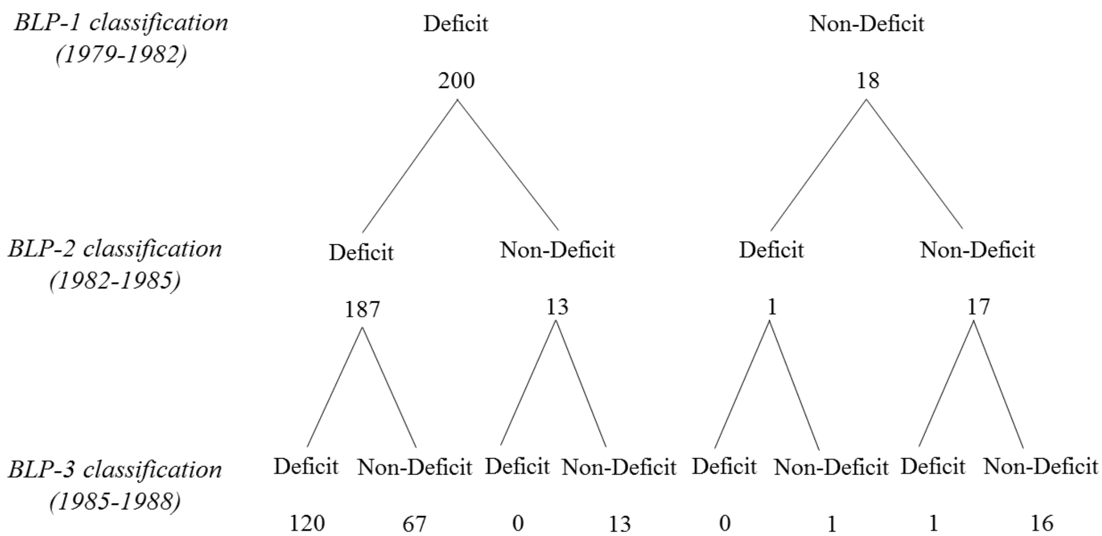
### 2.4.1 Identifying Access to Banking Services

When attempting to evaluate the impact of bank branch growth on agricultural production choices in a non-experimental setting, one of the main challenges is establishing a causal relationship. Unless specified otherwise in regulation, we would expect banks to selectively open new branches in the best agro-climatic regions in order to serve the most productive farmers. This selection bias likely amplifies the true impact of access to banking services when using Ordinary Least Squares (OLS). In contrast, banks may choose to open new branches in regions with lower baseline productivity, but higher growth potential, leading OLS to underestimate the true effects. In order to identify an exogenous source of bank growth, we adopt an instrumental variable approach which exploits central-government BLP regulations aimed explicitly at expanding rural banking infrastructure in India during the 1980s.

At the onset of BLP-1 in 1979, 92% of our sample districts were classified as deficit according to the RBI stipulated guidelines (see Figure 2.4 for a breakdown of districts by deficit status during each BLP period). BLP regulations identified districts as deficit if the ratio of their population per rural bank branch fell above the centrally-planned threshold of that period (stipulated using the national average at the time, and calculated using the 1981 India census population and the number of rural bank branches at the onset of the policy period)[15]. Licenses for new bank branches, were to be exclusively distributed to deficit districts. Initial evidence suggests that banks did in fact adhere to these policies. Specifically, we find that during BLP-1 (1979-1982), districts classified as deficit experienced an average growth of 69% in the number of rural bank branches – four times higher than that witnessed on average among non-deficit districts (see panel A of Figure 2.5). As shown in Figure 2.6, this significant growth rate in rural bank branches among deficit districts enabled unbanked regions across India to slowly converge over time to the centrally-planned target; securing the core objective of this rural banking expansion program.

[15] For a summary of the BLP regulations, see Table B.1.

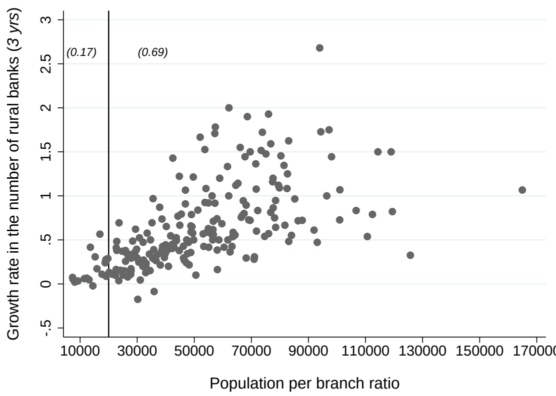
Figure 2.4: Classification of districts at the onset of each BLP period.



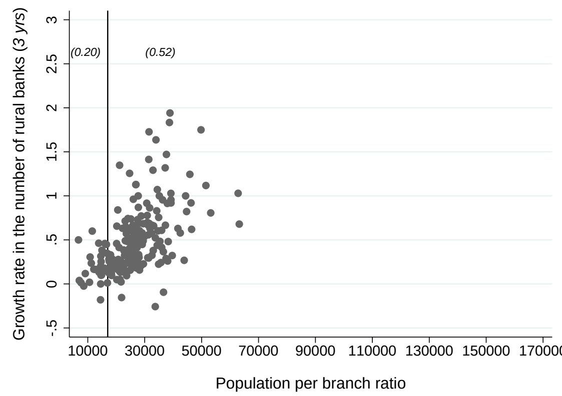

Notes: Classification of our complete sample of 218 districts for each BLP period. Districts were classified using their ratio of rural population per rural bank branch. This ratio was calculated using the 1981 Census of India rural population data and the total number of rural bank branches at the onset of the policy period (obtained from the Reserve Bank of India Basic Statistical Reserves). For the BLP-1 period, districts were classified as deficit if the ratio was above 20,000. This was revised down to 17,000 for the BLP-2 and BLP-3 period.

Figure 2.5: District growth in the number of rural banks during each BLP period.

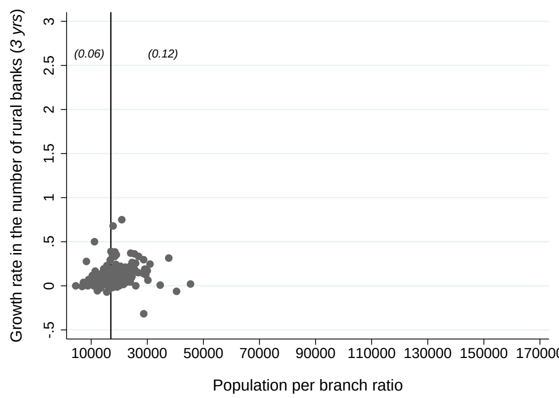
(a) Panel A: BLP-1 (1979-1982)




(b) Panel B: BLP-2 (1982-1985)



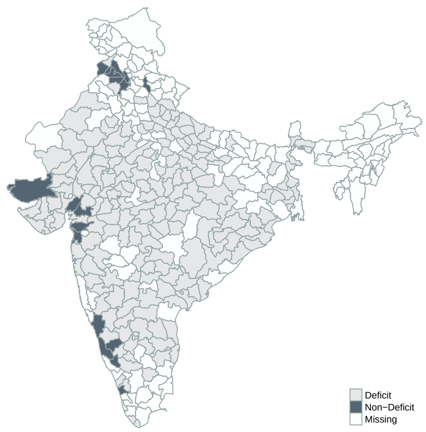

(c) Panel C: BLP-3 (1985-1988)



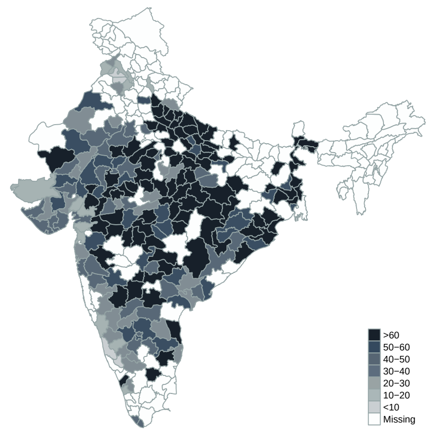

Notes: District-wise growth rates in each Panel is calculated over three years, corresponding to the policy periods. The vertical cutoff line corresponds to the stipulated target ratio of population per bank branch for each BLP period; 20,000 for BLP-1 and 17,000 for BLP-2 and BLP-3. Average growth rates of non-deficit and deficit districts are reported in parentheses on the left and right of the policy cutoff line respectively. Data on 218 districts.

Figure 2.6: Mapping of district classification and population per bank branch ratio at the onset of each BLP period.

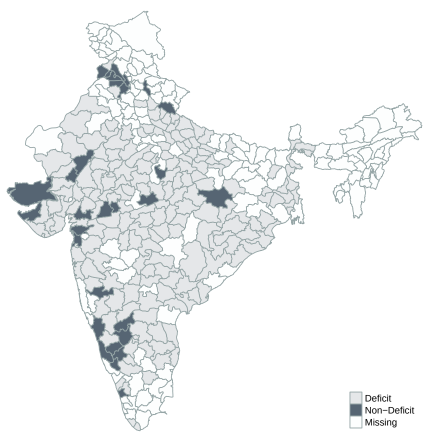
(a) Panel A1: BLP-1 classification (1979-1982)



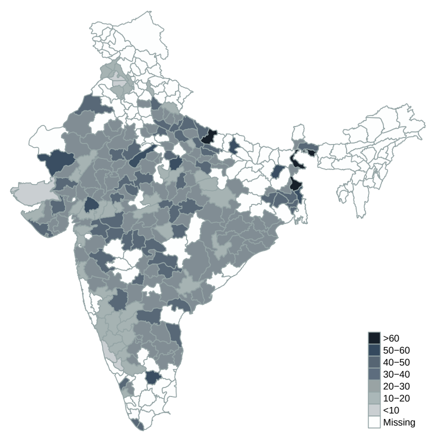

(b) Panel B1: Population per branch ratio (1979)



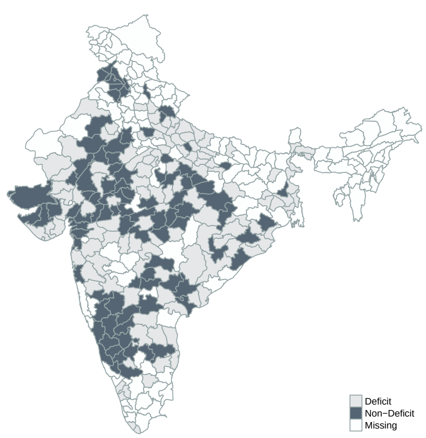

(c) Panel B1: BLP-2 classification (1982-1985)



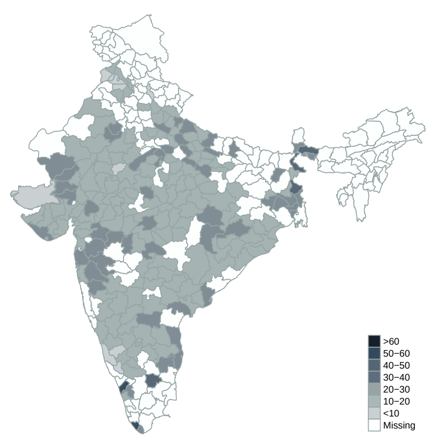

(d) Panel B2: Population per branch ratio (1982)




(e) Panel C1: BLP-3 classification (1985-1988)




(f) Panel C2: Population per branch ratio (1985)




Notes: Classification of deficit status and the ratio of population per rural bank branch for our complete sample of 218 districts at the onset of each BLP period. For the BLP-1 period, districts were classified as deficit if the ratio was above 20,000. This was revised down to 17,000 for the BLP-2 and BLP-3 period.

We leverage the exact regulatory targets classifying districts as deficit at the onset of each consecutive BLP period during the 1980s, in order to generate a time-varying instrument for bank growth at the district level. Specifically, we exploit the exogenous shift in bank growth imposed by the policies when reclassifying districts. For instance, the 188 of our sample districts classified as deficit during BLP-2 (1982-1985) would have experienced an average growth rate of 52% during this three year period. As of 1985, at the onset of BLP-3 (1985-1988), 36% of these districts changed status to non-deficit, halting their rural bank branch growth down to an average of only 6% over the next three years (see Figure 2.4 and Figure 2.5 for the classification of districts and growth in rural bank branches respectively).

We demonstrate the validity and strength of our identification by modeling the number of bank branches in a district within a given year as a function of its deficit status during each BLP period:

$$BankBranches_{it} = \sum_{j=1}^{3} \beta\Big(Def_{ijt} \times BLP_{jt}\Big) + \alpha_i + \eta_t + \delta_s \times t + \epsilon_{it}, \tag{2.1}$$

where $i$ is the district, $s$ is the state, $j$ is the BLP period, and $t$ is the year. $Def_{ijt}$ is a binary indicator which takes the value 1 if district $i$ is classified as deficit in period $j$ and 0 otherwise. $BLP_{jt}$ is a binary indicator which takes the value 1 for each year $t$ which overlaps with the given period $j$ and 0 otherwise. We control for district fixed effects - $\alpha_i$, time effects - $\eta_t$, and include state specific time trends - $\delta_s \times t$.

Given that we are specifically interested in capturing bank growth at the district level, and that each BLP period is implemented over three years, we adapt the identification specified in equation (2.1) to estimate the following growth rate model:

$$BankGrowth_{ij} = \sum_{j=1}^{3} \beta\Big(Def_{ij} \times BLP_j\Big) + \eta_j + \delta_s \times j + \epsilon_{ij}, \tag{2.2}$$

where $i$ is the district, $s$ is the state, $j$ is the BLP period. $BankGrowth_{ij}$ is measured as the change in the number of rural bank branches from the onset to the end of each three year BLP period[16]. Our instruments of interest are the three interaction terms between $Def_{ij}$ and $BLP_j$, which identify whether a district is classified as deficit in each BLP period separately. As in equation (2.1) we control for time effects - $\eta_j$, and state specific time trends - $\delta_s \times j$ (district fixed effects are accounted for when

[16]Specifically, $BankGrowth_{ij}{=}\big(BankBranches_{it} - BankBranches_{i,t-3}\big)/BankBranches_{i,t-3}$

taking first differences).

In order to ensure that the BLP regulations guiding rural bank growth expansion was not correlated with other factors of the rural economy potentially influencing agricultural growth during this period, we perform a series of placebo tests. We are particularly interested in ruling out factors such as infrastructure, access to markets, and preferential rates of finance to agriculture from the priority sector lending policies ongoing in the 1980s. Using the specification outlined in equation (2.2), we show that the BLP guidelines classifying districts as deficit in banking services, were not correlated with growth in road length, markets, and the ratio of DFA to total outstanding credit. Additionally, we verify that the classification of deficit status during each BLP period is not correlated to trends in our agricultural outcome variables prior to the onset of the policy in 1979. This test is conducted by using the specification from equation (2.2), but with the dependent variable being the growth rate in our agricultural outcomes for the decade prior to the policy (1969-1978).

### 2.4.2 Estimating the Impact of Access to Banking Services

Estimating bank growth via our exogenous instruments, based on the regulatory guidelines classifying districts as deficit during each of the three consecutive BLP periods of the 1980s, we can then capture the true impact of improved access to banking services on agricultural production choices. Our main specification can be written as:

$$AgriGrowth_{ij} = \gamma_1 \widehat{BankGrowth_{ij}} + \gamma_2 X_{ij} + \eta_j + \delta_s \times j + \epsilon_{ij}, \tag{2.3}$$

where $i$ is the district, $s$ is the state, and $j$ is the BLP period. The dependent agricultural indicators – production, input usage, and crop choice – are measured as growth rates for each three year BLP period. Our coefficient of interest, which captures the effect of improved access to banking services in a district, is $\gamma_1$ on the endogenous variable of $BankGrowth_{ij}$ (previously estimated using our instruments identified in equation (2.2)). $X_{ij}$ is a control variable for exogenous rainfall shock, measured as the change in annual rainfall over the course of each BLP period. Additionally, we control for time effects - $\eta_j$, and state specific time trends - $\delta_s \times j$ (district fixed effects are accounted for when taking first differences)[17].

In order to further verify the accuracy of our model, we conduct two main robustness tests. First, we estimate the model when removing 10% of districts exhibiting the highest bank growth rate. This enables us to confirm that our results are not confined to a select few districts with exponentially high growth rates in improved access to banking services. Second, we estimate the model by limiting the time period to the first two BLPs (BLP-1 and BLP-2). At the onset of BLP-3 in 1985, the IRDP amended its guidelines such that financial assistance was provided based on poverty levels (see Table B.1 for a summary of the timeline and changes to the IRDP). By excluding BLP-3, we show that our results are not confounded to the implementation of this other major welfare program also ongoing during the 1980s.

### 2.4.3 Interaction of Access to Banking and Weather

As a particular focus to evaluating the impact of access to improved banking services on agricultural production choices, we are interested in capturing the relationship between bank growth and exogenous weather outcomes. Access to banking services could either amplify or attenuate the impact of rainfall on agricultural production choices. Under favorable rainfall conditions, easing liquidity constraints could enable farmers to invest in inputs and therefore achieve higher yield levels. Under unfavorable conditions such as droughts, farmers could use financial services to mitigate their potential losses. We test for these hypotheses by allowing for a differential effect of rural bank growth and lagged rainfall within the following regression model:

$$\begin{aligned} AgriGrowth_{ij} =& \gamma_1 \widehat{BankGrowth_{ij}} + \gamma_2 \widehat{\Big(BankGrowth_{ij} \times LagRainfall_{ij}\Big)} \\ & + \gamma_3 X_{ij} + \eta_j + \delta_s \times j + \epsilon_{ij}, \end{aligned} \tag{2.4}$$

where $i$ is the district, $s$ is the state, and $j$ is the BLP period. The dependent agricultural indicators are measured as growth rates for each three year BLP period. The change in lag rainfall is measured over a three year period, based on the year preceding the onset of the BLP period (for instance with BLP-1 (1979-1982), the change in lag rainfall is calculated from 1978 to 1981). As in equation (2.3), we control for exogenous rainfall - $X_{ij}$, time effects - $\eta_j$, and state specific time trends -

[17]The level form for equation (2.3) can be written as: $AgriOutcome_{it} = \gamma_1 \widehat{BankBranches_{it}} + \gamma_2 X_{it} + +\alpha_i + \eta_t + \delta_s \times t + \epsilon_{it}$ where $i$ is the district, $s$ is the state, and $t$ is the year.

$\delta_s \times j$ (district fixed effects are accounted for when taking first differences)[18].

## 2.5 Results

### 2.5.1 Bank Compliance to BLP Regulations

As reported in a number of papers documenting the rural bank branch expansion program of the 1980s (Burgess and Pande, 2005; Fulford, 2013; Kochar, 2011), we find that the implementation of BLP regulations were predominantly satisfied. As shown in Figure 2.6, the distribution of deficit districts fell uniformly across India over the decade during which the BLPs were enforced, allowing the unbanked regions of the country to slowly converge to the centrally-planned policy target. This initial evidence is further confirmed by our results formally estimating growth in the number of rural bank branches over time using the explicit policy regulatory guidelines identifying deficit districts (see equation (2.2)). We find that bank growth was consistently higher among districts classified as deficit. The highest growth spur occurred during BLP-1 (1979-1982), wherein the number of rural bank branches in deficit districts grew by an additional 41% compared to those non-deficit (see column (3) of Table 2.2). This preferential rate fell to 27% during BLP-2 (1982-1985) and only 7% during the final BLP-3 (1985-1988) period.[19] The Kleibergen and Paap (2006) F-Statistic on the joint significance of our three interaction terms is approximately 40[20]. Conclusively, these results support the strength of our instruments in capturing exogenous variation in bank growth at the district level over time.

Importantly for our identification, we are also able to demonstrate that the regulations classifying districts as deficit and guiding bank branch expansion were not correlated to other potentially confounding factors of the rural economy. Specifically, we show that the deficit status of a district during each BLP period did not have any effect on the growth in both road coverage and the number of markets (see columns 4 and 5 of Table 2.2). Additionally, we may be concerned that the identification of deficit districts for the BLP program may have overlapped with the

[18]The analogous equation used to identify bank growth can be written as: $BankGrowth_{ij} = \sum_{j=1}^{3} \beta_1 (Def_{ij} \times BLP_j) + \sum_{j=1}^{3} \beta_2 (Def_{ij} \times BLP_j \times LagRainfall_{ij}) + \eta_j + \delta_s \times j + \epsilon_{ij}$ where $i$ is the district, $s$ is the state, and $t$ is the year.

[19]Columns (1) and (2) of Table 2.2 demonstrates the consistency of our results when excluding year effects and state specific time trends

[20]With approximately identically and independently distributed errors, the critical value for the weak instruments test based on maximal TSLS bias relative to OLS of 0.05 at 5% significance level is 13.91 (Stock and Yogo, 2005).

identification of districts benefiting from targeted finance to agriculture under the priority sector lending program also enforced centrally during the 1980s. We find the growth in the ratio of DFA to total outstanding credit (the policy target of the priority sector lending program) is uncorrelated with our instruments (see column 6 of Table 2.2); which we take as evidence that the two policies were in fact implemented independently. Finally in an additional set of placebo tests (reported in Table 2.3), we demonstrate that there does not exist any pre-trends between the classification of districts as deficit during each of the BLP periods and growth in our agricultural indicators during the decade prior to the program (1969-1978)[21]. This is crucial in determining that our instruments.

[21]Due to lack of data on our indicators for machinery (pumps and tractors) prior to 1977, these variables are excluded from this placebo test.

Table 2.2: Bank compliance to BLP rules and placebo tests (1979-82, 1982-85, 1985-88).

| | Panel A: Compliance | | | Panel B: Placebo | | |
|---|---|---|---|---|---|---|
| *Growth in* | Number of Rural Banks (1) | Number of Rural Banks (2) | Number of Rural Banks (3) | Road length (4) | Markets (5) | Ratio of DFA to total credit (6) |
| deficit District * BLP-1 | 0.586*** | 0.517*** | 0.407**** | 0.036 | 0.026 | 0.092 |
| | (0.036) | (0.050) | (0.046) | (0.039) | (0.026) | (0.060) |
| deficit District * BLP-2 | 0.424*** | 0.325*** | 0.267*** | -0.050 | 0.058 | 0.043 |
| | (0.031) | (0.043) | (0.042) | (0.038) | (0.039) | (0.041) |
| deficit District * BLP-3 | 0.014 | 0.058*** | 0.056** | 0.022 | -0.013 | 0.003 |
| | (0.017) | (0.015) | (0.023) | (0.016) | (0.033) | (0.030) |
| Kleibergen-Paap F-statistic | 157.957 | 52.145 | 40.669 | 1.381 | 1.109 | 1.091 |
| Observations | 632 | 632 | 632 | 632 | 599 | 626 |
| Districts | 218 | 218 | 218 | 218 | 210 | 218 |
| Time Fixed Effect | No | Yes | Yes | Yes | Yes | Yes |
| State Time Trend | No | No | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates are based on model outlined in equation (2.2). Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on the three interaction terms. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level.

Table 2.3: Effect of BLP classification on the growth in agricultural indicators in the decade prior to program (1969-78).

| | Output | | Inputs | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Land | Irrigation | Seeds | Fertiliser | | |
| *Pre BLP Growth in*: | Yield (1) | Production (2) | GCA (3) | GIA (4) | HYV (5) | Nitrogen (6) | Potassium (7) | Phosphate (8) |
| deficit District * BLP-1 | 0.048 | 0.006 | -0.018 | 0.090 | -0.722 | 0.111 | -0.521 | 1.092* |
| | (0.078) | (0.096) | (0.025) | (0.130) | (1.014) | (0.354) | (2.107) | (0.633) |
| deficit District * BLP-2 | -0.220 | -0.295 | -0.014 | -0.406 | -0.191 | 0.000 | -0.882 | 0.465 |
| | (0.153) | (0.188) | (0.021) | (0.373) | (0.977) | (0.417) | (1.665) | (0.631) |
| deficit District * BLP-3 | -0.070 | -0.094 | 0.019 | -1.245 | 2.842 | -0.494 | -10.339 | 0.449 |
| | (0.069) | (0.095) | (0.021) | (1.174) | (2.586) | (0.629) | (8.293) | (0.672) |
| Kleibergen-Paap F-statistic | 1.613 | 1.229 | 0.812 | 0.594 | 1.010 | 0.335 | 0.720 | 1.138 |
| Observations | 629 | 629 | 629 | 581 | 551 | 622 | 568 | 622 |
| Districts | 217 | 217 | 217 | 201 | 214 | 196 | 214 | 216 |
| Time Fixed Effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State Time Trend | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates are based on model outlined in equation (2.2). Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on the three interaction terms. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level.

### 2.5.2 Agricultural Production and Investment in Inputs

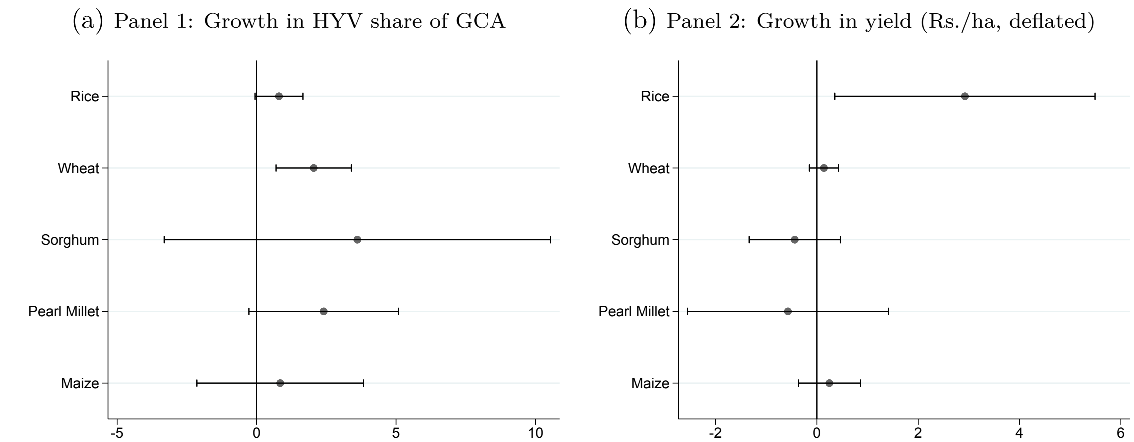
Improving access to financial services at the district level, by building additional rural bank branches, appears to have significantly increased agricultural yield and production. Specifically, we find that in response to a 1% growth in banks, aggregate yield increased by 0.42% during a three year BLP period (see column (1) of Table 2.4). In this study, we are specifically interested in identifying the pathways by which access to financial services enabled this improvement in agricultural production. One such pathway is by alleviating liquidity constraints, thereby enabling the adoption of inputs previously deemed unaffordable. In order to address this hypothesis, we consider investment in a range of agricultural inputs, including – land, irrigation, seeds, fertilizer, and machinery.

Our results on growth in inputs, reported in Table 2.4, suggest that a rise in agricultural yield can be at least partially attributed to a significant shift in the use of HYV seeds. This evidence corroborates a liquidity constraint hypothesis, as HYV seeds would have been more expensive then traditional varieties. High yielding varieties were known to be especially productive under favorable conditions of water supply and fertilization. It is therefore somewhat surprising that we do not detect a change in the use of irrigation and fertilizers. We cannot however reject a re-optimization of these inputs towards HYVs, as our indicators for fertilizer and irrigation are aggregated across all crops at the district level.

High yielding varieties emerged on the market in India following the green revolution of the 1960s in developing countries. The first of these improved varieties were focused towards cereal crops. In the VDSA, data on HYVs during the 1980s is therefore limited to rice, wheat, sorghum, pearl millet and maize. Figure 2.7 shows a breakdown by crop of the growth in area share of GCA grown with HYVs as well as the associated growth in yield. We find that while the area share of wheat increased significantly, this is not reflected in yield growth. This may be attributed to the fact that HYV wheat would have been available to farmers since the 1960s and if not regularly replaced by new seeds (the overwhelming majority of farmers re-use seeds from the previous year harvest) the additional productivity gains from these may have already started to fall back. On the other hand, we find that rice; which would have only entered the market in the early 1970s, has a large gain in yield for only a marginal increase in area share grown as HYV.

Machinery, especially tractors, are a known crucial input for productivity gains

Figure 2.7: Impact of access to financial services on area share and yield of HYV crops (1979-82, 1982-85, 1985-88).




Notes: Estimates are based on model outlined in equation (2.3). Standard errors are clustered at the district level. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level (Non-missing district observation per crop; Rice:$N$=171, Wheat:$N$=192, Sorghum:$N$=133, Pearl Millet:$N$=99, Maize:$N$=162).

on farms. It is with respect to this type of large investment that access to finance is often hailed as a poverty alleviation tool. Our results, however, do not find a significant improvement in the number of pumps and tractors with increased access to financial services. This is not so surprising when we compare the average loan amount to the cost of a tractor. Using India Census data on the total number of landholdings in 1981, we calculate the average loan size per farm to be approximately 700 Rupees in the early 1980s and rising to 2,000 Rupees by the end of that decade. A tractor, during the 1980s, would have cost approximately 10,000 Rupees – at least 5 times as much as the average loan.

These results are robust to excluding both outliers (see panel A of Table B.3) as well as limiting our sample to the first two BLP periods prior to the IRDP amendment providing financial assistance based on poverty levels (see Table B.4). Interestingly, the OLS estimates across all our specifications are much smaller then those from the IV. This trend is consistent with the hypothesis that banks may be choosing high productive borrowers based on their current level of production rather then their potential growth.

Table 2.4: Impact of access to financial services on agricultural output and inputs (1979-82, 1982-85, 1985-88).

| | Output | | Inputs | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Land | Irrigation | Seeds | Fertilizer | | | Machinery[a] | |
| *Growth in*: | Yield (1) | Production (2) | GCA (3) | GIA (4) | HYV (5) | Nitrogen (6) | Potassium (7) | Phosphate (8) | Pumps (9) | Tractors (10) |
| Panel A: OLS | | | | | | | | | | |
| Bank Growth | 0.091* | 0.078 | -0.018 | 0.071* | 0.224 | -0.089 | -0.113 | -0.281** | 1.760 | -0.207 |
| | (0.055) | (0.063) | (0.022) | (0.036) | (0.188) | (0.097) | (0.084) | (0.141) | (1.386) | (0.331) |
| Panel B: IV-TSLS | | | | | | | | | | |
| Bank Growth | 0.421*** | 0.476*** | 0.058 | 0.103 | 0.478*** | -0.119 | 0.538 | -0.362 | -0.285 | 0.150 |
| | (0.146) | (0.168) | (0.049) | (0.106) | (0.168) | (0.313) | (0.407) | (0.575) | (0.414) | (0.602) |
| Kleibergen-Paap F-statistic | 40.059 | 40.059 | 40.059 | 40.059 | 40.059 | 40.059 | 40.059 | 40.059 | 20.651 | 20.618 |
| Observations | 632 | 632 | 632 | 632 | 632 | 632 | 632 | 632 | 321 | 315 |
| Districts | 218 | 218 | 218 | 218 | 218 | 218 | 218 | 218 | 204 | 204 |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State Time Trend | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates are based on model outlined in equation (2.3). Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on our three instruments. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level. For a description of each variable source and construction, refer to Table B.2.[a]Availability of data for machinery is limited to growth in the first two BLPs (1979-82, 1982-85).

### 2.5.3 Crop Choice

Access to financial services may have served farmers not only by alleviating immediate liquidity constraints, but also by providing an opportunity to smooth consumption over the agricultural season and thereby engage to riskier but more profitable production choices. We attempt to capture this second pathway by assessing the effect of India's social banking program on patterns of crop choice. We consider four categories of crops – high volatility, rain sensitive, cash based, and grown in winter – which are all characterized by en element of risk in their return to investment.

Table 2.5: Impact of access to financial services on crop choice, (1979-82, 1982-85, 1985-88).

| *Growth in (Area share of)*: | High-Volatility (1) | Rain-Sensitive (2) | Cash-Crops (3) | Winter-Crops (4) |
|---|---|---|---|---|
| Panel A: OLS | | | | |
| Bank Growth | 0.044 | 0.032 | -0.102 | 0.025 |
| | (0.048) | (0.032) | (0.091) | (0.034) |
| Panel B: IV-TSLS | | | | |
| Bank Growth | 0.173 | -0.108 | 0.391** | 0.366*** |
| | (0.323) | (0.114) | (0.172) | (0.138) |
| Kleibergen-Paap F-statistic | 40.003 | 40.463 | 40.199 | 40.246 |
| Observations | 631 | 625 | 630 | 627 |
| Districts | 218 | 215 | 217 | 216 |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| State Time Trend | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates are based on model outlined in equation (2.3). Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on our three instruments. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level. For a description of each variable source and construction, refer to Table B.2.

Our first two indicators of crop choice are based on yield variability. In a first measure, we capture high–volatility crops; those whose yields perform above average under favorable conditions, but also suffer from above average losses when under resource stress. As can be seen in column (1) of Table 2.5, improved access to financial services does not appear to change the share of GCA grown with high–volatility crops. Our second measure, captures rain–sensitive crops; those whose yields were especially sensitive to exogenous rainfall shocks. This sensitivity to rainfall, would have been particularly relevant in a rain-fed agricultural system; the case of India during the 1980s. Our results suggest however, that farmers did not change their allocation of land towards crops most sensitive to rainfall in response to improved financial services (see column (2)).

For small-scale farmers who rely on their agricultural produce to feed their household, moving away from subsistence crops (for example rice and wheat) to cash crops (such as cotton or sugarcane), can be considered risky. While cash crops are often seen as more profitable, they are also more susceptible to market price fluctuations. Access to financial services however, appears to have provided farmers with the opportunity to take on this risk. Specifically, we find that a 1% increase in the number of rural banks during a three year BLP period, is associated with an increase of 0.39% in the growth rate of GCA allocated to cash crops (see column (3)).

As a final measure of crop choice, we consider crops grown in the winter Rabi season (October to March). Since this season does not receive any monsoon rainfall, these crops are largely dependent on artificial irrigation. Despite this additional cost, engaging in double cropping (that is, sowing crops in both the summer and winter season) has the potential to significantly improve agricultural production. As reported in column (4) of Table 2.5, growth in banks significantly increased the area share of winter crops; by approximately 0.37% within a three year period[22]. Taken together, these results tentatively suggest that banks did provide farmers with a opportunity to take on additional risk in their production choices.

As in the analysis for agricultural production and investment in inputs, we verify that our results on crop choice are not dependent on outliers. Results from this test are reported in Table B.5 and show that all trends and their associated level of significance remains constant when using a reduced sample of districts excluding those with the highest growth rate in number of banks. Additionally, we also conduct our analysis on a reduced time period for the first two BLPs (see Table B.6). While the result on winter crops is consistent in this sample, we loose magnitude and significance on our estimate of cash crops. This may be explained by the fact that adapting crop allocation is a slow process, and considering only a six year period is insufficient to capture change.

[22] Among those classified as cash crops only linseed, soybeans, rapeseed, and mustard are planted in the winter season. The correlation between the growth rates of cash- and winter-crops is positive but weak, with a Pearson correlation coefficient for the sample period is 0.29

### 2.5.4 Production Choices and Weather

In 1998, more than 60% of the cropped area in India was still depended solely on monsoon rainfall (Organization, 1998). Depending on the location, the monsoon rains are expected between June and September. According to Kumar et al. (2004), the highest concentration of rain-fed agriculture in the Western and Southern regions of India is for oilseed, grain, and cotton cultivation, while in the East is it predominantly for rice. Year-to-year fluctuations in monsoon rainfall directly impacts the variability of the summer Kharif season (July to October) production (Parthasarathy et al., 1988). Furthermore, the monsoon also indirectly affects crop production during the winter Rabi season (October to March), by providing stored soil moisture and irrigation.

Access to financial services could amplify or attenuate the impact of rainfall on agricultural output. Under favorable rainfall conditions, easing liquidity constraints could enable farmers to invest in inputs and therefore achieve higher yield levels. Under unfavorable rainfall conditions such as droughts, farmers could use financial services to mitigate their potential losses (for instance by accessing additional sources of irrigation). We test for these hypotheses by allowing for a differential effect of rural bank growth on the relationship between lagged rainfall[23] and our agricultural indicators; including production, input use, and crop choice respectively.

We find that the relationship between agricultural production and lagged rainfall is elastic. Assuming the growth rate of rural banks to be zero, an increase in lagged rainfall by 1% is associated with a 1.31% to 1.59% rise in the growth of yield and production respectively (column (1) and (2) of Table 2.6). This positive relationship is not surprising, as growing seasons overlap and water is stored from one season to the next for irrigation. However, our coefficient of interest in this analysis, is the interaction term between bank growth and lagged rainfall. Our results suggest a significant negative relationship for both yield and production. We take this as conclusive evidence that banks serve to attenuate the potential losses from exogenous negative rainfall shocks. However, banks do not seem to promote further growth or amplify yields following a positive rainfall period.

Among agricultural inputs, we also find an attenuating relationship between rain-

[23]The first BLP period is defined from 1979 to 1982. The growth in lagged rainfall for this period is therefore calculated for the years 1978 and 1981. The analogous process is carried out when computing the lagged rainfall growth for the second and third BLP-period.

fall and the growth in irrigated area (column (4) of Table 2.6). Since monsoon rainfall is collected and stored for the Rabi season, lagged rainfall is positively related to GIA. The negative coefficient on the interaction between lagged rainfall and growth in rural banks suggests that access to financial services enabled farmers to irrigate land even following a period of drought. In this case, stored rainfall is likely substituted with more costly groundwater pumped from wells. We find no evidence for differential effects on the use of land, HYVs, fertilizer, or machinery.

Table 2.7 summarizes the differential effect of bank growth on the relationship between crop choice and lagged rainfall. We find no statistical evidence for a differential effect of bank growth on the changes in area share allocated to high–volatility and rain–sensitive crops (column (1) and (2) respectively) in the year following a negative rainfall. With respect to cash crops, the positive relationship with bank growth remains, but we find no evidence for a differential effect related to lagged rainfall (column (3)). As explained previously, winter crops depend largely on stored water for irrigation. Therefore, it is not surprising to find a positive effect of lagged rainfall on the area share of winter crops (column (4)). The negative coefficient on the interaction term suggests that following poor rainfall, rural bank growth enabled farmers to continue engaging in double cropping. This result is again consistent with the attenuating effect of access to financial services on the relationship between lagged rainfall and gross irrigated area.

Table 2.6: Impact of access to financial services on agricultural output and inputs with lag rainfall (1979-82, 1982-85, 1985-88).

| | Output | | Inputs | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Land | Irrigation | Seeds | Fertilizer | | | Machinery[a] | |
| *Growth in:* | Yield (1) | Production (2) | GCA (3) | GIA (4) | HYV (5) | Nitrogen (6) | Potassium (7) | Phosphate (8) | Pumps (9) | Tractors (10) |
| Panel A: OLS | | | | | | | | | | |
| Bank Growth | -0.015 | -0.042 | -0.019 | 0.036 | 0.190 | -0.176 | -0.151 | -0.349** | 0.683 | -0.098 |
| | (0.048) | (0.059) | (0.020) | (0.039) | (0.163) | (0.112) | (0.098) | (0.159) | (1.107) | (0.225) |
| Bank Growth × Lag Rainfall | -1.157*** | -1.351*** | -0.025 | -0.430** | -0.492 | -1.032** | -0.116 | -0.750 | -10.556* | 1.980 |
| | (0.351) | (0.469) | (0.065) | (0.170) | (0.395) | (0.480) | (0.457) | (0.541) | (6.075) | (2.216) |
| Lag Rainfall | 0.524* | 0.698* | 0.056 | 0.251** | 0.262 | 0.127 | -0.520* | -0.379 | 5.195** | -3.128 |
| | (0.296) | (0.396) | (0.042) | (0.102) | (0.188) | (0.363) | (0.281) | (0.384) | (2.269) | (2.669) |
| Panel B: IV-TSLS | | | | | | | | | | |
| Bank Growth | 0.443** | 0.452** | 0.046 | 0.068 | 0.488*** | -0.058 | -0.129 | -0.625 | -0.596 | -0.311 |
| | (0.187) | (0.210) | (0.045) | (0.099) | (0.178) | (0.406) | (0.415) | (0.593) | (1.171) | (0.923) |
| Bank Growth × Lag Rainfall | -2.725*** | -3.127*** | -0.012 | -0.973*** | -0.478 | -0.918 | -0.502 | -0.171 | -0.511 | -0.517 |
| | (0.814) | (1.088) | (0.115) | (0.250) | (0.491) | (0.739) | (0.790) | (0.901) | (4.379) | (2.636) |
| Lag Rainfall | 1.312*** | 1.586** | 0.063 | 0.497*** | 0.317* | 0.101 | -0.345 | -0.692 | -1.119 | -1.810* |
| | (0.486) | (0.656) | (0.039) | (0.118) | (0.171) | (0.438) | (0.396) | (0.524) | (1.424) | (0.988) |
| Kleibergen-Paap F-statistic | 21.354 | 21.354 | 21.354 | 21.354 | 21.354 | 21.354 | 21.354 | 21.354 | 9.241 | 9.620 |
| Observations | 632 | 632 | 632 | 632 | 632 | 632 | 632 | 632 | 321 | 315 |
| Districts | 218 | 218 | 218 | 218 | 218 | 218 | 218 | 218 | 204 | 204 |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State Time Trend | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates are based on model outlined in equation (2.4). Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on our three instruments. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level. For a description of each variable source and construction, refer to Table B.2.[a] Availability of data for machinery is limited to growth in the first two BLPs (1979-82, 1982-85).

Table 2.7: Impact of banking infrastructure on crop choice with lag rainfall (1979-82, 1982-85, 1985-88).

| *Growth in (Area share of)*: | High-Volatility (1) | Rain-Sensitive (2) | Cash-Crops (3) | Winter-Crops (4) |
|---|---|---|---|---|
| Panel A: OLS | | | | |
| Bank Growth | 0.057 | 0.008 | -0.119 | -0.013 |
| | (0.058) | (0.027) | (0.095) | (0.032) |
| Bank Growth $\times$ Lag Rainfall | 0.325 | -0.216** | 0.177 | -0.411** |
| | (0.258) | (0.096) | (0.337) | (0.173) |
| Lag Rainfall | -0.234 | -0.010 | -0.569** | 0.154 |
| | (0.187) | (0.065) | (0.270) | (0.142) |
| Panel B: IV-TSLS | | | | |
| Bank Growth | 0.333 | -0.103 | 0.327** | 0.471*** |
| | (0.311) | (0.107) | (0.165) | (0.149) |
| Bank Growth $\times$ Lag Rainfall | 0.423 | -0.238 | -0.346 | -1.154*** |
| | (0.530) | (0.165) | (0.360) | (0.431) |
| Lag Rainfall | -0.221 | -0.023 | -0.244 | 0.585** |
| | (0.264) | (0.059) | (0.154) | (0.235) |
| Kleibergen-Paap F-statistic | 21.326 | 21.739 | 21.548 | 21.605 |
| Observations | 631 | 625 | 630 | 627 |
| Districts | 218 | 215 | 217 | 216 |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| State Time Trend | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates are based on model outlined in equation 2.4. Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on our three instruments. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level. For a description of each variable source and construction, refer to Table B.2.

## 2.6 Conclusion

This chapter studies the production effects of a major banking infrastructure program, in the context of rural India in the 1970s and 80s. We digitize data on rural branch expansion at the district-year level from the Reserve Bank of India's Basic Statistical Reports, and investigate whether faster growth in banking services affected agricultural output, inputs, crop choice, as well as the lagged effects of weather shocks. Our results indicate this is indeed the case. Agricultural yield and production both reacted positively to bank branch growth. In terms of magnitude, a 1% growth in bank branches over a 3-year program period translates to a 0.41% rise in yields at the district level.

This effect is driven by a greater use of higher-yielding cereal varieties, cash crops, as well as multiple cropping methods. For instance, a 1% growth in rural banks increased the share of gross cropped area cultivated with cash crops by approximately 0.39% over a program period. This suggests access to banking services may have allowed farmers to take on more risk, by shifting towards crops more susceptible to market price fluctuations. Finally, we find that bank growth weakens the lagged effects of unfavorable weather shocks, through greater use of irrigation.

In estimating the production effects of India's social banking program, we have not taken into account the program's costs, which are substantial (Fan et al. 2008). We have, however, systematically investigated the channels underlying the earlier documented effects on poverty alleviation (Burgess and Pande 2005 ;Fulford 2013; Kochar 2011). Importantly from a policy point of view, the results indicate that improved access to banking services has the potential to benefit rural communities, not only through better consumption smoothing, but through meaningful impacts on a range of production choices.

# Bibliography

**Aghion, Philippe and Patrick Bolton**, "A theory of trickle-down growth and development," *The Review of Economic Studies*, 1997, *64* (2), 151–172.

**Ashraf, Nava, Xavier Giné, and Dean Karlan**, "Finding missing markets (and a disturbing epilogue): Evidence from an export crop adoption and marketing intervention in Kenya," *American Journal of Agricultural Economics*, 2009, *91* (4), 973–990.

**Banerjee, Abhijit V and Andrew F Newman**, "Occupational choice and the process of development," *Journal of political economy*, 1993, *101* (2), 274–298.

**Beaman, L, D Karlan, B Thuysbaert, and C Udry**, "Self-Selection into Credit Markets: Evidence from Agriculture in Mali," *National Bureau of Economic Research.*, 2014, *No. w20387.*

**Burgess, R and R Pande**, "Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment," *American Economic Review*, 2005, *95* (2), 780–795.

**Conley, TG and CR Udry**, "Learning About a New technology: Pineapple in Ghana," *American Economic Review*, 2010, *100* (1), 35–69.

**Demirgüç-Kunt, Asli, Leora F Klapper, Dorothe Singer, and Peter Van Oudheusden**, "The global findex database 2014: Measuring financial inclusion around the world," 2015.

**Duflo, E, M Kremer, and J Robinson**, "Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya," *American Economic Review*, 2011, *101* (6), 2350–2390.

**Dupas, Pascaline, Dean Karlan, Jonathan Robinson, and Diego Ubfal**, "Banking the Unbanked? Evidence from three countries," *American Economic Journal: Applied Economics*, 2018, *10* (2), 257–97.

**Fan, S, A Gulati, and S Thorat**, "Investment, Subsidies, and Pro-poor Growth in Rural India," *Agricultural Economics*, 2008, *39* (2), 163–170.

**Fulford, Scott L**, "The effects of financial development in the short and long run: Theory and evidence from India," *Journal of development Economics*, 2013, *104*, 56–72.

**Hanna, Rema, Sendhil Mullainathan, and Joshua Schwartzstein**, "Learning through noticing: Theory and evidence from a field experiment," *The Quarterly Journal of Economics*, 2014, *129* (3), 1311–1353.

**Karlan, Dean, Robert Osei, Isaac Osei-Akoto, and Christopher Udry**, "Agricultural decisions after relaxing credit and risk constraints," *The Quarterly Journal of Economics*, 2014, *129* (2), 597–652.

**Kistler, Robert, Eugenia Kalnay, William Collins, Suranjana Saha, Glenn White, John Woollen, Muthuvel Chelliah, Wesley Ebisuzaki, Masao Kanamitsu, Vernon Kousky, van den Dool Huug, Jenne Roy, and Fiorino Michael**, "The NCEP NCAR 50 year reanalysis," *Bulletin of the American Meteorological Society*, 2001, *82* (2), 247–268.

**Kleibergen, Frank and Richard Paap**, "Generalized reduced rank tests using the singular value decomposition," *Journal of Econometrics*, 2006, *133* (1), 97 – 126.

**Kochar, A**, "The Distributive Consequences of Social Banking: a Microempirical Analysis of the Indian Experience," *Economic Development and Cultural Change*, 2011, *59* (2), 251–280.

**Kumar, H and R Somanathan**, "Mapping Indian Districts Across Census Years, 1971-2001," *Economic and Political Weekly*, 2009, *44* (41/42), 69–73.

**Kumar, Krishna K., Rupa K. Kumar, R. G. Ashrit, N. R. Deshpande, and J. W. Hansen**, "Climate impacts on Indian agriculture," *International Journal of Climatology*, 2004, *24* (11), 1375–1393.

**Muchow, R.C.**, "Comparative productivity of maize, sorghum and pearl millet in a semi-arid tropical environment II. Effect of water deficits," *Field Crops Research*, 1989, *20* (3), 207 – 219.

**Organization, Central Statistical**, "Compendium of Environment Statistics," Technical Report, Central Statistical Organization, Department of Statistics, Ministry of Planning and Programme Implementation, Government of India: New Delhi 1998.

**Panagariya, A**, "Bank Branch Expansion and Poverty Reduction: A comment," Technical Report, Mimeo, Columbia University 2006.

**Parthasarathy, B.A., A.A. Munot, and D Kothawale**, "Regression model for estimation of Indian food grain production from Indian summer rainfall," 03 1988, *42*, 167–182.

**Rurinda, J., P. Mapfumo, M.T. van Wijk, F. Mtambanengwe, M.C. Rufino, R. Chikowo, and K.E. Giller**, "Comparative assessment of maize, finger millet and sorghum for household food security in the face of increasing climatic risk," *European Journal of Agronomy*, 2014, *55*, 29 – 41.

**Singh, B.R. and D.P. Singh**, "Agronomic and physiological responses of sorghum, maize and pearl millet to irrigation," *Field Crops Research*, 1995, *42* (2), 57 – 67.

**Stock, James and Motohiro Yogo**, *Testing for Weak Instruments in Linear IV Regression*, New York: Cambridge University Press, 2005.

**Suri, T**, "Selection and Comparative Advantage in Technology Adoption," *Econometrica*, 2011, *79* (1), 159–209.

# Chapter 3

# Consumption-savings decisions with interdependent preferences. Staying ahead or catching up?

## 3.1 Introduction

Status seeking and habit formation are important characteristics of human behavior (Smith, 1759; Veblen, 1899; Duesenberry, 1949). A growing number of empirical studies account for inter-household comparisons and find measurable effects on consumption choices (Attanasio and Low, 2004; Maurer and Meier, 2008; Ravina, 2008; Drechsel-Grau and Schmid, 2014; Alvarez-Cuadrado et al., 2016). The empirical results are typically obtained from the estimation of log-linearized Euler equations, derived under a preference specification that allows for relative concerns with respect to a predefined reference group. The crucial problem with the identification of peer effects models of this type is related to the reflection problem of Manski (1993): A priori, it is difficult to distinguish the endogenous effect of peer expenditure on household consumption from unobserved exogenous and correlated effects. Inconsistency from exogenous peer effects arises if members of the reference group share characteristics that affect their consumption choice in a similar manner. For example, the age cohort of households may be a determinant of reference group affiliation which also affects expenditure profiles. If the households in a reference group face disturbances that affect their expenditure in a similar way due to common unobservable traits, the peer effects model is inconsistent due to correlated effects. For example, regional fluctuations and economic growth may affect permanent incomes and thereby expenditures within a reference group in a similar way.

In this chapter, I estimate the effect of expenditure disparity within a reference group on household consumption choices. To account for the reflection problem, I instrument expenditure disparity with the share of households in the reference group who receive windfall income. Here, windfall income is defined as unexpected income gains from inheritances, gifts, or lottery wins above EUR 2,500[1]. To the best of my knowledge, this is the first study that makes use of unexpected income shocks from inheritances, gifts, and lottery wins as an instrument for average expenditure disparity. The approach is motivated by empirical findings of Kuhn et al. (2011) who show that lottery winners increase expenditures for durable and visible goods. Furthermore, the neighbors of lottery winners were found to increase car related consumption expenses.

I show empirically that windfalls are not anticipated and increase consumption growth only in the years after they are realized. In conventional life-cycle models, transitory income gains have negligible impact on expenditure as households are assumed to smooth consumption over their lifetime. The sensitivity of consumption growth to windfall income in my data could be explained by high discount rates or liquidity constraints. Since windfall incomes increase consumption expenditure, the share of households who receive unexpected income gains is positively correlated with consumption disparity, and therefore a relevant instrument.

Other things held constant, suppose a household receives windfall income. Assume the arrival rate of windfalls depends on household-specific characteristics but not on realized windfall incomes within a reference group. In other words, this event does not impact the expectations of other rational households in the reference group to win the lottery, make an inheritance, or receive unexpected gifts. Then, the realization of windfall income shocks does not affect other households' expected lifetime income –which rules out direct effects on consumption and ensures instrumental validity. Furthermore, realizations of unexpected windfall income shocks should not be determined by economic growth, regional economic fluctuations, or other types of correlated effects that affect the expenditure of all households. While the size of inheritances and gifts undoubtedly correlates with e.g. economic growth, I treat arrival rates of unexpected gifts, lottery wins and mortality rates in a modern soci-

[1] This threshold is determined by the data set. Households are asked if they received unexpected windfall income from inheritances, gifts, or lottery wins exceeding EUR 2,500 in the previous year.

ety with a welfare state as exogenous[2]. Although the realization of windfall income shocks is uncorrelated across households, fluctuations in windfall shock realizations over time may covary with changes in observable common traits within reference groups. For example, it could be argued that the probability of receiving windfall income depends on exogenous characteristics such as the age of a household –a potential determinant of reference group affiliation. An endogeneity problem arises if the change in a variable such as age affects changes in both consumption choices and windfall income realizations. To mitigate endogeneity problems from exogenous effects, I employ a variety of reference group specifications based on both demographic and regional characteristics. Moreover, reference group aggregates of demographic characteristics are included along region and reference group fixed effects to control for exogenous effects.

To pin down the direction of comparisons, I decompose the effect of average peer expenditures into disparity to those with higher (i.e. disadvantageous disparity) and lower (i.e. advantageous disparity) expenditures. Envious preferences may be driven by upward or downward comparisons in that only the expenses of households above or below in the expenditure distribution matter. The results indicate that expenditure growth is positive in the distance to others higher up in the distribution. Likewise, increases in the distance to households with lower expenditure lead to reduction in expenditure. The relative size of these effects varies across reference group specifications. For reference groups defined by education, age-cohort, and cohabitation status, the elasticity of expenditure to changes in disadvantageous disparity is about 0.2. The elasticity of expenditure to changes in advantageous disparity is approximately 0.22.

The empirical results are derived from a life-cycle framework with forward looking, consumption smoothing agents as presented for example in Browning and Crossley (2009). To account for effects of others' expenditures on household consumption, the utility function is augmented by external habits represented by the average expenditure distance to other households in the reference group. I show that under technical assumptions the optimal consumption path can be represented by an Euler

[2]Between the years 2000 and 2012, the average deflated windfall income is EUR 46,581. I assume the threshold of EUR 2,500 is low enough to rule out business cycle effects on the probability of inheriting. Large gifts may be given to reduce future inheritance taxes. Different to conventional inheritances, the arrival rate of large gifts is arguably affected by correlated effects. In a robustness check, I restrict the instrument to lottery wins and inheritances. The results do not change qualitatively.

equation. This approach builds results of Dynan (2000) who studies consumption choices with internal habits.

Maurer and Meier (2008) employ a similar theoretical framework. Different to my approach, they estimate the effect of average expenditure changes and do not allow for differential peer effects dependent on the position of the household in the expenditure distribution. They attempt to overcome part of the reflection problem related to correlated effects by including the stratification variables in the empirical model as additional regressors. Since it cannot be ruled out that unobserved demographic information correlates with aggregated expenditures, a potential consumption externality may be spurious. To solve this endogeneity problem, they exploit that optimal consumption growth rates need to be consistent within peer groups. The resulting additional equilibrium conditions allow to estimate peer effects indirectly as a *social multiplier* operating through peer-group averages of the standard explanatory variables. In contrast, I attempt to overcome the reflection problem by directly instrumenting for the endogenous regressor.

This chapter is closely related to the studies of Drechsel-Grau and Schmid (2014) and in particular Alvarez-Cuadrado et al. (2016). Using the same data, Drechsel-Grau and Schmid (2014) find that a 1% increase in peer expenditures induces an increase in household expenditures by 0.3%. Instead of instrumental variables, their approach relies on state-year time trends to control for unobserved correlated effects. The similarity of their result suggests that both estimation methods are comparable in controlling for the reflection problem. Different to this study, they do not find evidence for downward looking comparisons.

Alvarez-Cuadrado et al. (2016) follow the GMM-estimation approach outlined by Ravina (2008) and Maurer and Meier (2008) and allow for both habit formation and interdependent preferences. Using Spanish data, their results indicate that utility from consumption services stems in equal parts from peer group, past, and own consumption. They try to attenuate correlated effects by including measures of the local unemployment rate and the interest rate faced by the reference group. Their results are robust across various reference group definitions. Different to this study, they do not distinguish between up- and downward comparisons and rely on control variables to account for correlated effects. Again, my results are qualitatively similar to theirs.

The remainder of the chapter is structured as follows. The life-cycle model with inter-household preferences is described in Section 3.2. Section 3.3 summarizes the data and the construction of subsamples for OLS and instrumental variable estimation. The empirical strategy with focus on the instrument and the construction of reference groups is presented in Section 3.4. Section 3.5 contains the results. Section 3.6 concludes.

## 3.2 The life-cycle model with peer group effects

Consider a household $i$ choosing aggregate consumption expenditure $c$ in each year $t$ to maximize an inter-temporal time-separable utility function that depends in part on interpersonal comparisons to a continuum of other households. The optimization problem subject to a set of budget constraints can be written as:

$$\max_{\{c_{it+s}\}_{s=0}^{T-t}} U_i = \mathbb{E}_t\Big[\sum_{s=0}^{T-t}\delta^s u(\tilde{c}_{it+s}, \mathbf{x_{it+s}})\Big] \quad s.t. \quad \begin{aligned} c_{it+s} + a_{it+s} =& (1+r_{it+s})a_{it+s-1} + y_{it+s} \\ a_{iT} \geq& 0, \end{aligned} \tag{3.1}$$

where $0 < \delta < 1$ is the discount factor, $\mathbf{x}$ denotes a vector of observed characteristics or taste-shifters[3], $r$ the risk-free interest rate at which households can lend and borrow, $a$ the household's assets, and $y$ disposable non-interest income. The expectations operator $\mathbb{E}_t$ is associated with the households subjective probability distribution. $T - t$ is the length of the remaining life and $u(.)$ the current or instantaneous utility function. Following MaCurdy (1982), the income process is described by:

$$y_{it} = \zeta'\mathbf{z_{it}} + y_{it}^p + \omega_{it} \qquad \text{where} \qquad y_{it}^p = y_{it-1}^p + \eta_{it}. \tag{3.2}$$

The vector $\mathbf{z}$ consists of exogenous variables which determine earnings. Shocks to permanent income $y^p$ are represented by $\eta$. In this formulation, $\omega \geq 0$ represents *i.i.d.* transitory income shocks –explicitly windfall income from lottery wins, gifts, and inheritances. Assume transitory windfall shocks are rare events and increase contemporaneous consumption due to large discount rates[4]. In equation (3.1), let $\tilde{c}$

[3] Utility is separable across leisure and consumption choices. Employment status and annual work hours are included in $\mathbf{x}$ to proxy for leisure.

[4] Alternatively, I could assume $T - t$ is small relative to the income shock. Consumption levels reflect expectations about the size and time of e.g. future inheritances. Assuming the exact time and size of the inheritance is uncertain, consumption growth is on average positive once the windfall

denote consumption services that depend on household consumption and aggregate expenditures of relevant others. To obtain a simple log-linear approximation of the Euler equation, $\tilde{c}$ is linear in consumption expenditure,

$$\tilde{c}_{it} = c_{it} - \gamma(c_{-it}, c_{it-1}), \tag{3.3}$$

where $\gamma(c_{-it}, c_{it-1})$ captures interpersonal expenditure comparisons. Envious preferences imply that consumption services are affected by the expenditure of others. In the simplest specification of interpersonal preferences, $\gamma(c_{-it}) = \theta\bar{c}_{-it}$ is the mean of the expenditure distribution. Alternatively –to model asymmetric interdependent preferences– the mean expenditure of others can be decomposed into the average distance to those who spend more than $i$ and those who spend less. Let $D$ and $S$ denote disadvantageous and advantageous expenditure disparity such that:

$$\begin{aligned} \gamma(c_{-it}, c_{it-1}) =& \alpha \int_{c_{it-1}}^{\infty} (x - c_{it-1}) \mathrm{d}F_t(x) + \beta \int_{0}^{c_{it-1}} (c_{it-1} - x) \mathrm{d}F_t(x) \\ =& \alpha D(c_{-it}, c_{it-1}) + \beta S(c_{-it}, c_{it-1}), \end{aligned} \tag{3.4}$$

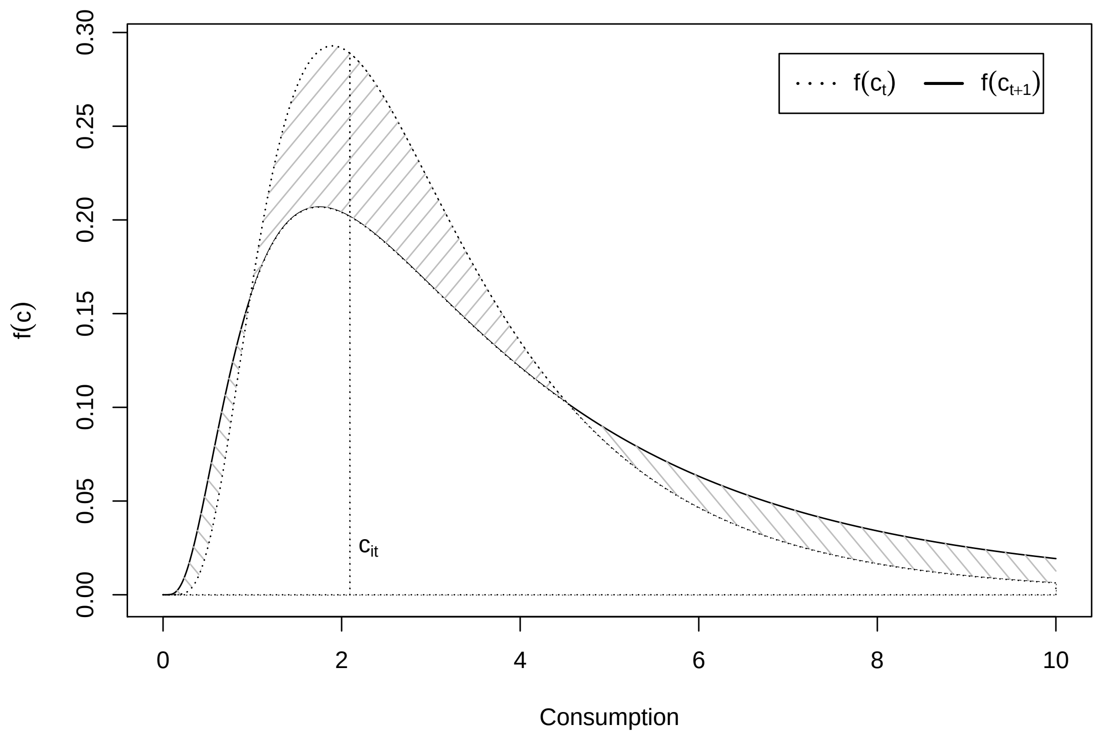
where $F_t$ denotes the consumption expenditure distribution in period $t$. Equation (3.4) allows to model upward and downward comparisons explicitly. Households with upward-looking preferences such as envy are unaffected by the average distance to others with lower consumption ($\alpha > 0, \beta = 0$). Likewise households with downward-looking preferences (e.g. pride) are affected only by the consumption distance to those with relatively lower consumption ($\alpha = 0, \beta < 0$). Note that the disparity variables in equation (3.4) differ from the familiar measures of relative deprivation and relative satisfaction[5].

The specification suggested here imposes the assumption that households expe-

shock is realized. Kuhn et al. (2011) find empirical evidence for this assumption in the sense that lottery winners increase car consumption.

[5]The measures of relative satisfaction and relative deprivation introduced by Yitzhaki (1980) are defined as the average distance to those with lower and higher income (here expenditure) respectively at a given point in time. Since in Yitzhaki's specification households choose expenditures simultaneously, the identification of an effect of others' contemporaneous expenditures requires knowledge of the life-time earnings process. Being agnostic about lifetime earnings, it cannot be empirically determined if a household is affected by contemporaneous expenditure choices of others, whether her consumption expenditures affect those of others, or if expenditures are governed by unobserved external shocks. The main difference between the specifications is that past (instead of present) expenditure of household $i$ is the reference point for relative comparisons.

Figure 3.1: Consumption disparity.




rience relative deprivation and satisfaction before choosing own consumption expenditure. The distribution of past consumption choices is observed by all households. Figure 3.1 visualizes the changes in expenditure disparity from the perspective of household $i$. The shaded area on the left of $c_{it}$ reflects a change in relative satisfaction; the shaded area on the right a change in relative deprivation. Prior to choosing consumption expenditure, each household observes the realization of windfall incomes $\omega$ in the population and predicts the spending of others. The household observes how her consumption in $t$ relates to predicted consumption choices of others and experiences the effect of expenditure disparity. Then, all households choose consumption simultaneously[6]. In equilibrium, $\partial U_i/\partial c_{it} = \partial U_i/\partial c_{it+1} = 0$, and capital markets allow households to transfer funds between periods so that $\mathrm{d}c_{it+1} = -(1 + r_{it})\mathrm{d}c_{it}$. Then, the first order condition for this optimization problem results in the following Euler equation:

[6]The proof of existence of an equilibrium for the dynamic case is beyond the scope of this study. Cole et al. (1992) show the existence of an equilibrium with interdependent preferences in a similar model.

$$\delta(1+r_{it+1})\left[\frac{\frac{\partial U_i}{\partial c_{it+1}}}{\frac{\partial U_i}{\partial c_{it}}}\right] = 1+e_{it+1}, \tag{3.5}$$

where $e_{it}$ denotes the expectational error of household $i$ which reflects innovations to income and the consumption distribution. Using the standard iso-elastic utility specification with $\sigma$ denoting the coefficient of relative risk aversion,

$$u(\tilde{c}_{it}, \mathbf{x_{it}}) = \exp(\xi'\mathbf{x_{it}})\frac{(\tilde{c}_{it})^{1-\sigma}}{1-\sigma}, \tag{3.6}$$

and substituting in (3.5), yields:

$$\delta(1+r_{it+1})\frac{exp(\xi'\mathbf{x_{it+1}})(\tilde{c}_{it+1})^{-\sigma} + \delta\kappa_{it+1}exp(\xi'\mathbf{x_{it+2}})(\tilde{c}_{it+2})^{-\sigma}}{exp(\xi'\mathbf{x_{it}})(\tilde{c}_{it})^{-\sigma} + \delta\kappa_{it}exp(\xi'\mathbf{x_{it+1}})(\tilde{c}_{it+1})^{-\sigma}} = 1+e_{it+1}, \tag{3.7}$$

where $\kappa_{it+1} = \alpha - (\alpha+\beta)F_{t+2}(c_{it+1})$ and $F_{t+2}(c_{it+1})$ denotes the rank of $c_{it+1}$ in the consumption distribution at time $t+2$. As shown in Appendix C, under a constant return on wealth, static expectations on the consumption distribution, and sufficiently small values for $\alpha$ and $\beta$, equation (3.7) can be expressed

$$\delta(1+r)\frac{exp(\xi'\mathbf{x_{it+1}})(\tilde{c}_{it+1})^{-\sigma}}{exp(\xi'\mathbf{x_{it}})(\tilde{c}_{it})^{-\sigma}} = 1+e_{it+1}. \tag{3.8}$$

Taking the natural logarithm, using the first difference operator and collecting terms yields:

$$\Delta\ln(\tilde{c}_{it+1}) = \overbrace{\frac{1}{\sigma}[\ln(\delta)+\ln(1+r)]}^{\mu} + \frac{1}{\sigma}\Delta\xi'\mathbf{x_{it+1}} - \underbrace{\frac{1}{\sigma}\ln(1+e_{it+1})}_{\varepsilon_{it+1}}. \tag{3.9}$$

To arrive at an optimality condition in terms of expenditure instead of consumption services, following Dynan (2000) and Muellbauer (1988), $\Delta\ln(\tilde{c}_{it+1}) = \Delta\ln(c_{it+1} - \alpha D(c_{-i,t+1}, c_{i,t}) - \beta S(c_{-i,t+1}, c_{i,t}))$ is approximated by:

$$\Delta\ln(\tilde{c}_{it+1}) \approx \Delta\ln(c_{it+1}) - \alpha\Delta\ln D(c_{-i,t+1}, c_{i,t}) - \beta\Delta\ln S(c_{-i,t+1}, c_{i,t}). \tag{3.10}$$

The correlation between the exact expression and the approximation in the data I use is relatively high when $\alpha$ and $\beta$ are small. For example, for observations where the exact expression is defined, the correlation is about 0.96 when $\alpha = \beta = 0.1$, about 0.8 with $\alpha = 0.3$ and $\beta = 0.2$, and about 0.54 when when $\alpha = 0.4$ and $\beta = 0.6$. Substituting equation (3.10) in (3.9), rolling back one period, and rearranging gives:

$$\begin{aligned}\Delta \ln(c_{it}) =& \mu + \Delta \ln \gamma(c_{-it}, c_{it-1}) + \frac{1}{\sigma}\Delta\xi'\mathbf{x_{it}} + \varepsilon_{it} \\ =& \mu + \alpha\Delta \ln D(c_{-i,t}, c_{i,t-1}) + \beta\Delta \ln S(c_{-i,t}, c_{i,t-1}) \\ &+ \frac{1}{\sigma}\Delta\xi'\mathbf{x_{it}} + \varepsilon_{it},\end{aligned} \tag{3.11}$$

where $\varepsilon_{it} = -\frac{1}{\sigma}\ln(1 + e_{it})$ and $\mu = \frac{1}{\sigma}[\ln(\delta) + \ln(1 + r)]$. Although the last equation relates consumption expenditures to their lagged value and consumption disparity, it should not be interpreted as a consumption function but an optimality condition. In each period, households choose consumption so that the marginal utility from consumption services today equals the expected discounted marginal utility from consumption services tomorrow. Since windfall shocks are *i.i.d.*, current windfall shocks contain no information about future windfall incomes. Everything else equal, with envious preferences ($\alpha > 0, \beta = 0$), a period $t$ windfall shock to another household with higher spending reduces consumption services. To smooth consumption services, the envious household $i$ chooses a higher expenditure than under selfish preferences ($\alpha = \beta = 0$). Assuming no further windfall and permanent income shocks in the following periods, consumption disparity and household expenditure decrease. By assumption, the arrival of a windfall shock increases expenditures of household $i$. Since increased consumption *ceteris paribus* also reduces relative deprivation, the increase in consumption following a windfall shock to household $i$ will be smaller compared to the case of selfish preferences. The remainder of this chapter is dedicated to the estimation of the parameters $\alpha$ and $\beta$ in equation (3.11) and the parameter $\theta$ in the simple case where interdependent preferences relate to the arithmetic mean.

## 3.3 Data

The German Socio Economic Panel (SOEP) provides data for more than 12,000 households formed by 20,000 individuals starting in 1984 and for East Germany following reunification in 1990. From 2002 onwards, a subsample of high income households[7] is included in the data to mitigate underrepresentation of top earners. Together with the large number of households followed over many years, the inclusion of top earners improves representativeness of income distributions. Over the years, new households were added to the data, some as refreshment to mitigate attrition, others to capture subpopulations such as migrants.

A representative income distribution and many years of data are indispensable for consistent estimation of log-linearized consumption Euler equations with preference interdependence. Attanasio and Low (2004) show that consistent estimation of log-linearized consumption Euler equations requires micro data covering a long time period to utilize large-T asymptotics. However, including data from years prior to 2002 reduces the representativeness of the reference group income distributions since top earners are underrepresented. Additionally, *windfall income*, the variable used to construct the instrument for consumption disparity is observed only from the year 2000 onwards. For these reasons, I restrict the analysis to all household heads for the years 2002 to 2012. Unfortunately, detailed information on consumption expenditure is only available for the year 2010. However, starting in 1992, respondents were asked whether they save part of their monthly disposable income. Those who answer *yes* are subsequently asked to state their monthly savings. Following Drechsel-Grau and Schmid (2014) I calculate monthly consumption expenditure as the difference between disposable income and savings.

Starting with 632,427 observations from 1984 to 2012, the above described restrictions lead to omission of 501,675 data points. Next, 1,739 observations without information on saving behavior are dropped. Of the remainder, 6,845 observations are excluded as they do not contain information on household income or report an income of zero. The seven cases in which savings exceed income, and the 2,131 cases in which individuals state positive savings but fail to report the amount saved in the follow up question are omitted. On average, 10,938 observations per year remain.

In every year, up to 100 reference groups by occupation and up to 50 by education are defined. Identification of the effect of changes in consumption disparity requires representativeness of the reference group consumption and income distributions. If a reference group contains less than five individuals, it is excluded from the sample for the given period. About 10% of the occupation reference groups across all

[7]The subsample consists of 1,224 households with monthly net household income of more than EUR 4,500.

years contain five or fewer individuals[8]. Reference groups by education distinguish at most 50 subgroups per year and include non-employed (i.e. out of the labor force and unemployed) individuals. Therefore, only about 1% of the subgroups by education contain less than the required number of observations. These observations are dropped.

For every household, the assessment of personal consumption disparity is assumed to depend on how lagged consumption compares to relevant others –the reference group. If reference groups are endogenous, they likely depend on demographic characteristics. Approximately 35% of respondents to the European Social Survey state that they do not compare to others. Those who compare name work colleagues (56%), friends (23%), family members (9%), and undefined others (12%) as their reference group (Clark and Senik, 2010). It can be argued that individuals compare their own standing to a group similar to them, a group they aspire to belong to in the future, their own consumption history, or a subset of the entire society perceived as representative for the region or country. In the empirical literature, reference groups are defined either across households who share observable characteristics or live in the same geographical region.

Since survey respondents are not asked if and to whom they compare to, the individual specific reference group cannot be identified directly from the data. Furthermore, as shown by Manski (1993), obtaining reference groups from observed behavior will make any social effects model hold by construction and thwart identification. Therefore, informed specification of the relevant reference groups is required and will be based on observable demographic characteristics. Specifically, reference groups are defined according to (i) occupation-age-gender (ii) occupation-age-cohabitation, (iii) education-age-gender, and (iv) education-age-cohabitation. Co-workers are the most frequently cited reference group. In specifications (i) and (ii), the measures of consumption disparity are calculated by the ten major occupation groups specified by the International Standard Classification of Occupations (ISCO). ISCO groups occupations mainly on the basis of the similarity of skills required to fulfill the tasks and duties of the jobs[9]. The age-cohorts are defined by individuals being younger

[8]In a non-reported robustness test, reference groups with less than 50 individuals are dropped. This change in the threshold did not qualitatively impact the results.

[9]The following 10 occupation types form reference groups: (1) legislators, senior officials and managers; (2) professionals; (3) technicians and associate professionals; (4) clerks; (5) service workers and shop and market sales workers; (6) skilled agricultural and fishery workers; (7) craft and related trades workers; (8) plant and machine operators and assemblers; (9) elementary occupations;

than 25, between 25 and 35, between 35 and 45, between 45 and 65, and over 65 years old at the time of the interview. Cohabitation indicates whether the individual is living together with a life partner. The first and second specification results in 100 separate reference groups. In specifications (iii) and (iv), individuals are categorized into groups dependent on whether they report less than 10, 10, 11, 12, or more than 12 years of education[10]. Combined with five age cohorts and gender or cohabitation, this results in a total of 50 reference groups. When occupation is used as a stratifying variable, the sample is restricted to employed individuals. If information on less than 50 households is available for a given year from the sample, the respective reference group is omitted for that year to achieve representative consumption distributions.

Table 3.1 provides summary statistics on the demographic variables used for reference group construction. Approximately two thirds are employed and one quarter are residents in the states of the former German Democratic Republic. Reference groups defined by occupation type contain on average between 204 and 414 individuals. Groups defined by education are about twice as large as those defined by occupation since the latter are restricted to employed household heads.

Table 3.2 summarizes the variables income, windfalls, and the consumption disparity measures. The indicator variable Windfall equals one if unexpected income above EUR 2,500 originating e.g. from lottery wins, inheritances, or gifts is received in a given year. The average adjusted and deflated disposable monthly household income is EUR 1,679 of which on average about EUR 200 are saved. I adjust income and consumption by the square root of the household size. For less than 3% of the observations monthly savings are zero. This number appears to be unreasonably small. Consequently, by construction the sample participants appear to be financially better off than the population they represent. Since sample selection bias cannot be ruled out, the results may not be representative.

(10) armed forces.

[10]Less than 10 years of school implies that the highest possible degree obtained is a *Hauptschulabschluss*. 10 and 11 years of schooling are required to achieve a *Realschulabschluss*. After 12 years of school, the *Abitur* can be achieved, which enables enrollment for tertiary education.

Table 3.1: Summary statistics for demographic variables.

| Variable | Mean | Std. Dev. | Min | Max | N |
|---|---|---|---|---|---|
| Year | 2006.98 | (3.2) | 2002 | 2012 | 120327 |
| Age | 52.5 | (16.5) | 17 | 102 | 120326 |
| Education (years) | 12.36 | (2.78) | 7 | 18 | 117147 |
| No. of children | 1.65 | (0.79) | 1 | 9 | 31943 |
| Cohabitation | 0.65 | (0.48) | 0 | 1 | 120300 |
| Hours (annual) | 1217.76 | (1144.29) | 0 | 6111 | 120326 |
| Employed | 0.61 | (0.49) | 0 | 1 | 120326 |
| East | 0.25 | (0.43) | 0 | 1 | 120327 |
| Male | 0.59 | (0.49) | 0 | 1 | 120327 |
| Size group: Occ.-age-gender | 204.7 | (141.24) | 5 | 646 | 71355 |
| Size group: Occ.-age-cohabitation | 207.53 | (158.97) | 5 | 665 | 71273 |
| Size group: Edu.-age-gender | 391.06 | (250.33) | 7 | 1089 | 117136 |
| Size group: Edu.-age-cohabitation | 414.1 | (280.71) | 5 | 1150 | 117122 |

Source: SOEP, v29.

Table 3.2: Summary statistics for key variables.

| Variable | Mean | Std. Dev. | Min | Max | N |
|---|---|---|---|---|---|
| Windfall | 0.03 | (0.18) | 0 | 1 | 120143 |
| Consumption | 1481.46 | (999.89) | 0 | 124558.09 | 120327 |
| Income | 1679.01 | (1288.18) | 0.94 | 127751.9 | 120327 |
| ln(reference consumption) | | | | | |
| (i) Occ.-age-gender | 7.36 | (0.25) | 6.37 | 8.46 | 73713 |
| (ii) Occ.-age-occupation | 7.36 | (0.26) | 6.35 | 8.81 | 73713 |
| (iii) Edu.-age-gender | 7.27 | (0.25) | 6.34 | 7.83 | 120327 |
| (iv) Edu.-age-occupation | 7.27 | (0.26) | 6.37 | 7.81 | 120327 |
| ln(disadvantageous disparity) | | | | | |
| (i) Occ.-age-gender | 5.53 | (1.07) | -11.03 | 8.27 | 68566 |
| (ii) Occ.-age-occupation | 5.52 | (1.08) | -10.51 | 8.68 | 68556 |
| (iii) Edu.-age-gender | 5.49 | (1.05) | -4.65 | 7.74 | 112669 |
| (iv) Edu.-age-occupation | 5.48 | (1.05) | -12.37 | 7.71 | 112652 |
| ln(advantageous disparity) | | | | | |
| (i) Occ.-age-gender | 4.95 | (1.61) | -14.92 | 10.79 | 68543 |
| (ii) Occ.-age-occupation | 4.93 | (1.62) | -7.39 | 10.82 | 68512 |
| (iii) Edu.-age-gender | 4.9 | (1.64) | -7.32 | 10.81 | 112644 |
| (iv) Edu.-age-occupation | 4.87 | (1.65) | -7.93 | 10.82 | 112649 |

Source: SOEP, v29.

## 3.4 Empirical Strategy

Suppose households have interdependent preferences in the sense that utility $u(c, \tilde{c})$ depends in part on own consumption $c$ and the outcomes (i.e. consumption or income) of relevant others, $\tilde{x}$. In recent years, various explicit functional specifications for $\tilde{c}$ have been suggested and tested. Luttmer (2005) finds that interpersonal comparisons drive the inverse relationship between average income and self-reported happiness, which suggests that utility decreases in the consumption expenditures of others. Fehr and Schmidt (1999) model preferences as a function of the households position in the payoff distribution. By letting $\tilde{c} = \alpha \sum_{i=1}^{n} \max\{c_{-i} - c_i, 0\} + \beta \sum_{i=1}^{n} \max\{c_i - c_{-i}, 0\}$ they distinguish between inequality averse and spiteful preferences in data from game-theoretic experiments. A growing number of empirical studies account for inter-household comparisons via $\tilde{c} = 1/(n-1)\sum_{j \neq i} c_j \equiv \bar{c}$ and find measurable effects of $\bar{c}$ on consumption choices (Attanasio and Low, 2004; Maurer and Meier, 2008; Ravina, 2008; Drechsel-Grau and Schmid, 2014; Alvarez-Cuadrado et al., 2016).

Assume additive and inter-temporal time-separable utility $U$ with instantaneous utility given by $u(c, \tilde{c}, x)$, in which $x$ is a vector of taste shifters. Under weak technical assumptions and a conventional iso-elastic utility specification, the condition which determines the optimal consumption path can be rearranged so that:

$$\begin{aligned} \Delta c_{ipt} &= \theta \Delta \tilde{c}_{pt} + \Delta x_{it}' \xi^* + \epsilon_{ipt} \\ \epsilon_{ipt} &= \chi_{pt} + \eta_{pt} + \varepsilon_{it}. \end{aligned} \tag{3.12}$$

Equation (3.12) relates changes in consumption to a set of taste shifters and the consumption choices of other households in a reference group $p$. As a rearranged Euler equation, (3.12) should be interpreted as an optimality condition instead of a consumption function. The parameter $\theta$ accounts for interdependent preferences such as envy or pride.

The crucial problem with the identification of $\theta$ is related to the reflection problem of Manski (1993): A priori, it is difficult to distinguish the endogenous effect of peer expenditure on household consumption from unobserved exogenous and correlated effects. Omitted variable bias from exogenous peer effects, denoted $\chi_{pt}$, arises if members of the reference group share characteristics that affect their consumption choice in a similar manner. It is an empirical fact, that consumption expenditures are hump-shaped in age (Carroll and Summers, 1991). At the same time, households may compare their expenditure to others in the same age cohort. Correlated changes in reference consumption could arise due to interdependent preferences or as a result of changes in aggregate age.

Furthermore, omitted variable bias arises if the households in a reference group face disturbances that affect their expenditure in a similar way due to common unobservable traits or correlated effects. In the error term of equation (3.12), $\eta_{pt}$

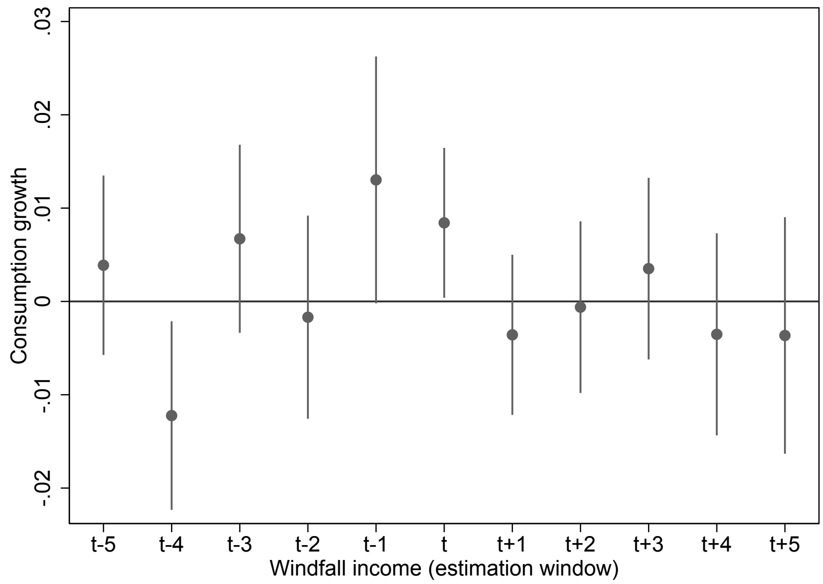
represents such correlated effects. Suppose aggregate household consumption correlates with macroeconomic conditions. Changes in economic growth then manifest in spurious correlation between household and average consumption expenditure. More generally, any omitted variable that is correlated both with changes in household and average consumption expenditure will lead to inconsistent estimates of $\theta$.

To address these threats to internal validity, I use an instrumental variable to estimate equation (3.12). A valid instrumental variable for $\tilde{c}$ must not contain information about changes in permanent income of household $i$ and, at the same time, provide exogenous variation in consumption expenditures of $i$'s reference group. Suppose windfall incomes such as inheritances, gifts, or lottery wins affect contemporaneous household consumption. Then, the share of households in a reference group which obtain unexpected windfall income in a given period may be a valid instrument for changes in reference group consumption $\Delta\tilde{c}$.

Households may have private information about the size of future gifts and bequests and forecast the time of arrival. Moreover, consumption choices throughout life may reflect the expectation of a future windfall. I assume households do not anticipate the precise date of arrival of a windfall shock, and that its realization causes an increase in contemporaneous consumption. Figure 3.2 plots the coefficients from a regression of consumption growth on a binary variable indicating the arrival of a windfall shock. Consumption growth in the period of a windfall shock increases by one percentage point at 10% significance. In the periods leading up to the windfall shock, changes in consumption growth are largely insignificant.

If the share of households who obtain windfall income is unaffected by household characteristics that move everyones consumption choice in a similar manner, omitted variable bias from exogenous effects is accounted for. For example, if comparison groups are assumed to be determined by demographic characteristics such as age, the share of households who obtain windfall incomes should be uncorrelated with average age in the population. To test the extent to which the instrument accounts for exogenous effects, I estimate the marginal effect of changes in the share of households who obtain windfalls on observable demographic variables. Table 3.3 shows that when both variables are aggregated at a regional level (i.e. German states), the relationship is insignificant. When this placebo test is conducted at reference group aggregation for the four specified reference groups, the coefficients remain insignificant at the 5% level for reference groups (ii) and (iv).

Figure 3.2: Effect of windfall income on consumption growth.




The share of households who obtain windfall income addresses endogeneity problems originating from correlated effects if the probability of receiving windfall income is independent of macroeconomic conditions. Undoubtedly, the value of gifts and bequests fluctuates with commodity and stock prices or, more generally, economic conditions. However, in a developed economy with a welfare state, the likelihood of obtaining unexpected income in a certain year should not be related to economic conditions. It is possible to test this hypothesis for some macroeconomic variables at the regional level. Panel B of Table 3.4 presents point estimates for the effect of changes in the share of households who obtain windfall incomes in a German state (*Bundesland*) on changes in income per capita, GDP per capita, the no. of businesses, the unemployment rate, and energy consumption. As expected, none of the coefficients is statistically significant.

Since windfall incomes obtained in reference group $p$ do not affect the permanent income of household $i$, changes in the share of households who receive windfalls should be an exogenous instrument for changes in average consumption and consumption disparity. In other words, the instrument should not directly affect utility and therefore not be part of a household's utility optimization problem. Even if household consumption increases in windfall income, the effect on others may depend on the nature of the windfall shock. For example, both lottery wins and regular

Table 3.3: Placebo test (exogenous effects). Relationship between demographic aggregates and windfall ratio 2002-2012.

| Growth in aggregate: | Age | Educ. | Children | Cohab. | Worker | Hours |
|---|---|---|---|---|---|---|
| States | -0.047 | -0.011 | -0.181 | 0.001 | -0.176 | -1.822 |
| | (0.074) | (0.055) | (0.179) | (0.168) | (0.254) | (2.086) |
| (i) Occ.-age-gender | 0.116*** | 0.070 | -0.097 | 0.386* | | -0.134 |
| | (0.024) | (0.051) | (0.072) | (0.183) | | (0.235) |
| (ii) Occ.-age-cohabitation | 0.029 | 0.042 | 0.164 | 0.120 | | -0.124 |
| | (0.059) | (0.128) | (0.145) | (0.194) | | (0.285) |
| (iii) Edu.-age-gender | -0.218* | 0.158*** | -0.280 | -0.412* | 0.041 | 0.839 |
| | (0.115) | (0.027) | (0.177) | (0.195) | (0.270) | (1.637) |
| (iv) Edu.-age-cohabitation | -0.164 | 0.183* | -0.211 | 1.253* | 0.497 | 2.431 |
| | (0.248) | (0.095) | (0.367) | (0.683) | (0.331) | (2.207) |

* significant at 10% ** significant at 5% *** significant at 1%. Standard errors clustered by reference group. Independent variable: ΔWindfall ratio, which indicates change in the share of households which obtained windfall incomes in a reference group. Source: SOEP, v29.

Table 3.4: Placebo test (correlated effects). Relationship between macroeconomic indicators and windfall ratio 2002-2012.

| *Dependent variable:* | ΔIncome/capita | ΔGDP/capita | ΔBusinesses | ΔUnemployment rate | ΔEnergy cons. |
|---|---|---|---|---|---|
| ΔWindfall ratio | 1,453.831 | 17,107.601 | -53.216 | 7.683 | 20.920 |
| | (1,522.162) | (16,113.194) | (73.131) | (5.959) | (92.092) |
| State FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 116 | 116 | 116 | 116 | 112 |

* significant at 10% ** significant at 5% *** significant at 1%. Standard errors clustered by state. ΔWindfall ratio indicates change in the share of households which obtained windfall incomes in a state. Source: SOEP, v29.

wage increases may temporarily increase consumption growth but may be perceived differently by others who try to keep up. Empirical evidence suggests that windfall shocks affect consumption choices of relevant others. Kuhn et al. (2011) find evidence for social effects of lottery prizes on the car consumption of neighbors of winners. Having an immediate neighbor win the lottery significantly raises the probability of a car purchase. Compared to the modest effects of lottery prizes on the consumption choices of winning households, the effect on neighbors is large.

In this study, I focus on the local average treatment effect of changes in consumption disparity caused by windfalls on household consumption choices. On average, about 3% of the sample population report to have received unexpected income of EUR 2,500 or more in a given year. The average value of a windfall shock during the period 2002 and 2012, deflated and adjusted for household size, is EUR 29,250. For comparison, the average adjusted and deflated monthly net disposable household income in the sample is EUR 1,679. Table 3.5 shows that changes in the share of households in the reference group who obtain windfall income are strongly related to the measures of consumption disparity for demographic reference group specifications. Under geographical reference groups, the first stage is not identified. Going forward, I restrict the analysis to reference groups defined by demographic characteristics. The Kleibergen and Paap (2006) rk statistic, distributed as chi-squared with one degree of freedom, exceeds the 5% critical value for specifications (i)-(iv) and tabulated minimal bias of the IV estimator relative to OLS. On all four specifications, the signs on the coefficients are as expected. This suggests that the instrument is strongly related to changes in aggregate consumption and consumption disparity for some reference groups.

Table 3.5: First Stage. Relationship between average reference consumption and windfall income.

| *Dependent variable:* | $\Delta\bar{c}_{-i,t}$ | $\Delta d_i(c_{i,t-1}, c_{-i,t})$ | $\Delta s_i(c_{i,t-1}, c_{-i,t})$ |
|---|---|---|---|
| States | -0.002 | 0.058 | 0.267 |
| | (0.022) | (0.217) | (0.374) |
| Kleibergen-Paap F-stat. | 0.01 | 0.07 | 0.51 |
| (i) Occ.-age-gender | 0.432*** | 1.736*** | -1.011*** |
| | (0.032) | (0.185) | (0.223) |
| Kleibergen-Paap F-stat. | 186.83 | 87.71 | 20.59 |
| (ii) Occ.-age-cohab. | 0.476*** | 1.615*** | -1.098*** |
| | (0.030) | (0.208) | (0.230) |
| Kleibergen-Paap F-stat. | 246.03 | 60.51 | 22.86 |
| (iii) Edu.-age-gender | 0.231*** | 1.191*** | 0.707*** |
| | (0.021) | (0.173) | (0.241) |
| Kleibergen-Paap F-stat. | 125.79 | 47.27 | 8.64 |
| (iv) Edu.-age-cohab. | 0.415*** | 1.435*** | -1.108*** |
| | (0.025) | (0.188) | (0.265) |
| Kleibergen-Paap F-stat. | 278.6 | 58.57 | 17.44 |
| Time FE | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes |
| Reference group FE | Yes | Yes | Yes |

* significant at 10% ** significant at 5% *** significant at 1%. Small-case letters indicate logarithms. $\Delta\bar{c}_{-i,t}$ is the growth rate of peer consumption, $\Delta d_i(c_{i,t-1}, c_{-i,t})$ is the growth rate of consumption disparity to others higher ranked in the expenditure distribution, $\Delta s_i(c_{i,t-1}, c_{-i,t})$ is the growth rate of consumption disparity to others lower ranked in the expenditure distribution. Independent variable: $\Delta Windfall_{i,t}$ indicates change in the share of households who obtain windfall incomes in a reference group-year. Source: SOEP, v29.

## 3.5 Results

Table 3.6 summarizes the relationship between changes in household consumption, windfall income, and average consumption for four different reference group specifications. The point estimates obtained from OLS in panel A do not indicate significant effects of windfall and average consumption on household consumption growth at conventional significance levels. Besides state, time, and reference group fixed effects, the regressions contain demographic control variables such as changes in age, education, employment status, or growth in annual hours worked. Reference group averages of all demographic control variables are included. The results in panel A contradict the findings of Drechsel-Grau and Schmid (2014) who report significant effects of changes in average consumption. The source for the discrepancy appears to be the inclusion of aggregated demographic control variables. By controlling for changes in reference group aggregates, omitted variable bias from exogenous effects may be mitigated –potentially at the cost of losing relevant variations in consumption expenditure. When this restriction is removed, the I find envious preferences for all reference group specifications.

Panel B contains point estimates obtained from instrumenting[11] average consumption expenditures with the proportion of households in the reference group who received windfall income. To avoid endogeneity, demographic household characteristics and reference group aggregates are omitted from the set of control variables employed in panel A. The coefficients on the change in windfall income suggest that a positive windfall shock is accompanied by an increase of 1% (at 10% significance) in consumption growth for the average household for most specifications. Different to panel A, when reference groups are defined by cohabitation and average consumption is instrumented, the point estimates indicate envious preferences. Surprisingly, reference groups defined by gender instead of cohabitation status do not confirm this finding. The discrepancy in results suggests that weighting household consumption expenditure by the square root of the number of individuals living in the household may lead to considerable measurement error. Even after adjusting for household size, consumption expenditure of a family household may not be comparable to expenditures of a single household. For this reason, I focus on interdependent preferences identified in comparisons between households who share the same cohabitation sta-

[11] All two-stage least squares IV estimates in this thesis are computed with the *ivreg2* package by Baum et al. (2002).

Table 3.6: Consumption with interdependent preferences and habits. Reference groups by occupation-age-gender.

| Dependent variable: $\Delta c_{i,t}$ | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| *Panel A. OLS* | | | | |
| $\Delta$Windfall income | 0.009 | 0.009 | 0.007 | 0.007 |
| | (0.006) | (0.006) | (0.005) | (0.005) |
| $\Delta\bar{c}_{-i,t}$ | -0.035 | 0.029 | -0.033 | 0.018 |
| | (0.024) | (0.022) | (0.036) | (0.034) |
| Demographic controls | Yes | Yes | Yes | Yes |
| Demographic aggregates | Yes | Yes | Yes | Yes |
| Observations | 52,601 | 52,555 | 91,035 | 91,040 |
| $\bar{R}^2$ | 0.024 | 0.024 | 0.019 | 0.019 |
| *Panel B. IV 2SLS* | | | | |
| $\Delta$Windfall income | 0.010* | 0.011* | 0.008 | 0.009* |
| | (0.006) | (0.006) | (0.005) | (0.005) |
| $\Delta\bar{c}_{-i,t}$ | -0.068 | 0.249** | -0.362 | 0.704*** |
| | (0.136) | (0.119) | (0.310) | (0.192) |
| Kleibergen Paap F-statistic | 186.581 | 246.574 | 125.749 | 278.593 |
| Reference group FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes |
| Observations | 53,613 | 53,569 | 91,185 | 91,184 |

* significant at 10% ** significant at 5% *** significant at 1%. Small-case letters indicate logarithms. Dependent variable: $\Delta c_{it}$ is household consumption growth. $\Delta\bar{c}_{-i,t}$ denotes growth in peer consumption. Reference groups according to (i) occupation-age-gender, (ii) occupation-age-cohabitation, (iii) education-age-gender, (iv) education-age-cohabitation. Demographic control variables are growth rates of age, age-squared, years of education, no. of adults in household, no. of children in household, annual work hours, cohabitation. Aggregates controls are the changes in the group averages of the demographic controls. Instrumented: $\Delta c_{-i,t}$. Excluded instrument: $\Delta Windfallratio$. Source: SOEP, v29.

tus.

The point estimate of about 0.25 in specification (ii) is of similar magnitude as the estimates reported in Drechsel-Grau and Schmid (2014) and Alvarez-Cuadrado et al. (2016) in comparable empirical models. The coefficient on the change in peer consumption of about 0.7 in specification (iv) is surprisingly large and suggests a relatively high elasticity of household consumption with respect to aggregate reference group consumption expenditure. The point estimates suggest that an increase in peer consumption of 1% –induced by windfall income obtained in the reference group– increases average household consumption by 0.25% or 0.7% dependent on the reference group specification. A potential reason for the large spread between the point estimates is that reference groups defined by education include more households and less groups, which results in a better approximation of the reference group consumption distributions. The Kleibergen Paap F-statistics suggest that for all specifications, the instrument is strongly related to the endogenous variable.

In Table 3.7 the effect of peer consumption is decomposed into the disparity to households with higher and lower consumption expenditure. Panel A contains the results obtained by OLS estimation. The point estimates on the change in windfall income are of similar magnitude as in the previous table and significantly positive for reference groups by cohabitation status. For all reference groups, the results suggest small but significant effects of advantageous and disadvantageous consumption disparity on household consumption expenditure. Households appear to have on average upward and downward looking preferences. In contradiction to Drechsel-Grau and Schmid (2014), the elasticity of household consumption with respect to advantageous consumption disparity is larger than the elasticity with respect to disadvantageous disparity. Taken together, the results suggest prideful and envious preferences, in that part of the household consumption expenditure serves the purpose of staying ahead of others lower in the consumption distribution as well as keeping up with others ranked higher in the distribution.

Panel B summarizes the results obtained by two-stage least squares IV estimation. Again for all specifications, a windfall income shock is associated with an increase in consumption growth by about 1%, which is significant for specifications (ii) and (iv). Consistent with the results reported in the previous table, the point estimates suggest interdependent preferences for reference groups defined by cohabitation. Increases in the disparity to those with higher consumption –induced by changes in the proportion of windfall incomes– causes the average household to increase consumption expenditure to keep up. Analogously, an increase in the disparity to others with lower consumption causes a reduction in household consumption expenditure. Since changes in household expenditures are related to variations in consumption disparity originating from changes in the share of unexpected windfall incomes, these coefficients imply prideful and envious preferences. The arrival of a windfall for one household does not affect permanent income for other households and therefore contains no information on own future advances. This fact rules out alternative explanations such as the *tunnel effect* of Hirschman (1973).

Consider column (iv) in panel B of Table 3.7. The elasticity of consumption to disadvantageous consumption disparity is about 0.2. A 1% increase in the consumption distance to those with the same level of education, cohabitation status, and age-cohort whose contemporaneous consumption exceeds the household's reference (i.e. past) consumption is associated with an increase in own consumption by about 0.2%. Likewise, the elasticity of consumption to advantageous disparity is about 0.22 and a 1% decrease in the consumption distance to those who reported smaller consumption levels in the previous year is associated with an increase in own consumption by about 0.22%. These point estimates suggest that the average individual prefers to keep up with and stay ahead of similar others in the consumption distribution. As in Table 3.6, the point estimates are smaller in magnitude in column (ii) in panel B with consumption elasticities of 0.07 and 0.09 with respect to disadvantageous and advantageous disparity. These results are surprising in that they suggest that households with interdependent preferences are affected at least as much by the expenditure distance to others who consume less as they are affected by the distance to those who consume more.

For some specifications, the coefficients on consumption disparity are asymmetric in size. Considering results from instrumental variable regressions reported in columns (ii) and (iv) of Table 3.7, the point estimates on advantageous consumption disparity are weakly larger. This asymmetry could reflect inherent preferences in that staying ahead of others in terms of consumption is more relevant than catching up. Alternatively, it may be driven by the shape of the consumption distribution. Suppose for example that the effect of others' consumption choices depends on the household's position in the income distribution. For example, if households with below average income have envious but not prideful preferences, and households with above average income have prideful but not envious preferences, then similar point estimates would emerge. In this case, the estimated prideful and envious preferences would not be representative for any household.

To account for heterogeneous interdependent preferences, I estimate the empirical model by reference group income quartile. Table 3.8 summarizes the results for occupation-age-cohabitation reference groups. Panel A contains the point estimates from OLS regression. Both the coefficient on average consumption and the measures of advantageous and disadvantageous consumption disparity appear to be similar across income quartiles. When consumption disparity is instrumented, the point estimates confirm that interdependent preferences are relatively consistent across

Table 3.7: Consumption with interdependent preferences and habits. Reference groups by occupation-age-gender.

| Dependent variable: $\Delta c_{i,t}$ | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| | *Panel A. OLS* | | | |
| $\Delta$Windfall income | 0.007 | 0.008* | 0.006 | 0.007* |
| | (0.005) | (0.005) | (0.004) | (0.004) |
| $\Delta d_i(c_{i,t-1}, c_{-i,t})$ | 0.030*** | 0.030*** | 0.043*** | 0.042*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $\Delta s_i(c_{i,t-1}, c_{-i,t})$ | -0.065*** | -0.061*** | -0.070*** | -0.068*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Demographic controls | Yes | Yes | Yes | Yes |
| Demographic aggregates | Yes | Yes | Yes | Yes |
| Observations | 50,774 | 50,655 | 89,701 | 89,681 |
| $\bar{R}^2$ | 0.116 | 0.114 | 0.119 | 0.119 |
| | *Panel B. IV 2SLS* | | | |
| $\Delta$Windfall income | 0.009 | 0.011** | 0.008 | 0.010** |
| | (0.006) | (0.005) | (0.005) | (0.004) |
| $\widehat{\Delta d_i}(c_{i,t-1}, c_{-i,t})$ | -0.027 | 0.071** | -0.074 | 0.204*** |
| | (0.035) | (0.034) | (0.064) | (0.052) |
| $\widehat{\Delta s_i}(c_{i,t-1}, c_{-i,t})$ | 0.067 | -0.092** | -0.128 | -0.222*** |
| | (0.062) | (0.045) | (0.087) | (0.064) |
| Kleibergen Paap F-stat. (dis) | 87.533 | 60.858 | 47.286 | 58.982 |
| Kleibergen Paap F-stat. (adv) | 20.474 | 22.802 | 8.570 | 17.475 |
| Demographic controls | Yes | Yes | Yes | Yes |
| Reference group controls | Yes | Yes | Yes | Yes |
| Observations | 52,605 | 52,559 | 90,544 | 90,520 |

* significant at 10% ** significant at 5% *** significant at 1%. Dependent variable: $\Delta(c_{it})$. $\Delta d_i(c_{i,t-1}, c_{-i,t})$ is the growth rate of consumption disparity to others higher ranked in the expenditure distribution, $\Delta s_i(c_{i,t-1}, c_{-i,t})$ is the growth rate of consumption disparity to others lower ranked in the expenditure distribution. Reference groups according to (i) occupation-age-gender, (ii) occupation-age-cohabitation, (iii) education-age-gender, (iv) education-age-cohabitation. Demographic control variables are first differences of age, age-squared, years of education, no. of adults in household, no. of children in household, average work hours per workday, cohabitation. Reference group controls are the changes in the group averages of the demographic controls. Instrumented: $\Delta c_{i,t-1}$. Excluded instrument: $\Delta Windfall_{-i,t}$. Source: SOEP, v29.

income quartiles. This result is inconclusive since the instrument is weak for some income quartiles. The tendency to keep up with others who consume more appears to be U-shaped in the household's rank in the income distribution.

Including non-employed households in the sample and defining reference groups according to years of education, age-cohort, and cohabitation suggests that preferences do not vary substantially with the position of the household in the group-specific income distribution. The point estimates by reference group income quartile

Table 3.8: Heterogeneity analysis by income quartile in the reference group income distribution. Reference groups by occupation-age-cohabitation.

| Dependent variable: $\Delta c_{i,t}$ | Reference group income quartile | | | |
|---|---|---|---|---|
| | $1^{st}$ quartile | $2^{nd}$ quartile | $3^{rd}$ quartile | $4^{th}$ quartile |
| *Panel A. OLS* | | | | |
| $\Delta\bar{c}_{-i,t}$ | 0.080* | 0.081** | 0.070* | 0.070 |
| | (0.045) | (0.035) | (0.037) | (0.046) |
| $\Delta d_i(c_{i,t-1}, c_{-i,t})$ | 0.064*** | 0.031*** | 0.030*** | 0.026*** |
| | (0.011) | (0.009) | (0.006) | (0.004) |
| $\Delta s_i(c_{i,t-1}, c_{-i,t})$ | -0.052*** | -0.063*** | -0.070*** | -0.081*** |
| | (0.004) | (0.004) | (0.005) | (0.005) |
| Demographic controls | Yes | Yes | Yes | Yes |
| Reference group controls | Yes | Yes | Yes | Yes |
| Observations | 12,281 | 13,124 | 13,180 | 12,070 |
| *Panel B. IV 2SLS* | | | | |
| $\widehat{\Delta\bar{c}}_{-i,t}$ | 0.075 | 0.559*** | 0.393** | 0.403* |
| | (0.220) | (0.195) | (0.191) | (0.234) |
| $\widehat{\Delta d}_i(c_{i,t-1}, c_{-i,t})$ | 0.066 | 0.253*** | 0.168** | 0.093** |
| | (0.074) | (0.086) | (0.081) | (0.047) |
| $\widehat{\Delta s}_i(c_{i,t-1}, c_{-i,t})$ | -0.126 | -0.328** | -0.156*** | -0.179* |
| | (0.175) | (0.138) | (0.053) | (0.093) |
| Kleibergen Paap F-statistic ($\Delta d_i$) | 35.014 | 13.052 | 8.246 | 20.816 |
| Kleibergen Paap F-statistic ($\Delta s_i$) | 1.514 | 4.893 | 13.527 | 7.474 |
| Observations | 13,218 | 13,543 | 13,495 | 12,303 |
| Reference group FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes |

* significant at 10% ** significant at 5% *** significant at 1%. Small-case letters indicate logarithms. Dependent variable: $\Delta(c_{it})$ is household consumption growth. $\Delta d_i(c_{i,t-1}, c_{-i,t})$ is the growth rate of consumption disparity to others higher ranked in the expenditure distribution, $\Delta s_i(c_{i,t-1}, c_{-i,t})$ is the growth rate of consumption disparity to others lower ranked in the expenditure distribution. Inequality measures calculated with reference groups according to occupation-age-cohabitation. Each coefficient stems from a separate regression where the sample is restricted to individuals in a quartile of the income distribution of their reference group. Demographic control variables are first differences of age, age-squared, years of education, no. of adults in household, no. of children in household, annual work hours, cohabitation. Reference group controls are the changes in the group averages of the demographic controls. Instrumented: $\Delta\bar{c}_{-i,t}$, $\Delta d_i(c_{i,t-1}, c_{-i,t})$, $\Delta s_i(c_{i,t-1}, c_{-i,t})$. Excluded instrument: $\Delta Windfall_{-i,t}$. Source: SOEP, v29.

for this specification are summarized in Table 3.9. Consider the results obtained by OLS in panel A. Again, when interdependent preferences are defined by the position of a household in the consumption distribution, prideful and envious preferences obtain for all reference group income quartiles. When average peer income is assumed to capture interdependencies, envious preferences obtain only for the bottom income quartile. The point estimates from two-stage least squares IV estimation are reported in panel B. The marginal effect of peer consumption changes drastically. For the top 75% of the income distribution, the point estimates suggest unreasonably strong envious preferences. Using the alternative preference specification, prideful and envious preferences obtain for the top 75% of the income distribution. Again, the results are not conclusive since for some specifications, the instrument is weak.

The classification by reference group income quartiles is arbitrary and pools households with substantially different income and consumption profiles. As a robustness check, I therefore restrict the subsamples to quartile position of the household in the overall income distribution in a given year. The results are reported in Table C.1 (for reference groups defined by occupation-age-cohabitation), and Table C.2 (for reference groups by education-age-cohabitation) of the Appendix. For the top half of the income distribution, the results are similar for both reference group specifications. Taken together, if the instrumental variables are strongly related to the endogenous variable, the evidence suggests that envious and prideful preferences obtain for most income quartiles.

## 3.6 Conclusion

This chapter demonstrates that interpersonal comparisons obtain for some reference group specifications when endogeneity problems stemming from correlated and exogenous effects are accounted for. Omitted variable bias from unobserved correlated and exogenous effects is the most important endogeneity problem for estimating Euler equations with peer effects. For example, unobserved economic growth may increase both household consumption and consumption disparity. To mitigate potential omitted variable bias from non-linear economic growth, I estimate a life cycle model using the share of windfall income in the reference group as an instrument for consumption disparity. To the best of my knowledge, this is the first study that makes use of unexpected income shocks from inheritances, gifts, and lottery wins as an instrument for consumption disparity. This approach is motivated by empirical findings of Kuhn et al. (2011) who show in a study on the effects of lottery outcomes that winners increased expenditures for cars and durables. I confirm the result of envious preferences with reference groups defined by occupation/education, age-cohort, and cohabitation status.

I decompose the effect of average consumption by similar others into consumption disparity to those with higher and lower consumption than household $i$. The aver-

Table 3.9: Heterogeneity analysis by income quartile in the reference group income distribution. Reference groups by education-age-cohabitation.

| | Reference group income quartile | | | |
|---|---|---|---|---|
| Dependent variable: $\Delta c_{i,t}$ | $1^{st}$ quartile | $2^{nd}$ quartile | $3^{rd}$ quartile | $4^{th}$ quartile |
| | *Panel A. OLS* | | | |
| $\Delta\bar{c}_{-i,t}$ | 0.201*** | 0.012 | 0.060 | 0.046 |
| | (0.061) | (0.047) | (0.054) | (0.073) |
| $\Delta d_i(c_{i,t-1}, c_{-i,t})$ | 0.083*** | 0.043*** | 0.040*** | 0.026*** |
| | (0.013) | (0.011) | (0.007) | (0.004) |
| $\Delta s_i(c_{i,t-1}, c_{-i,t})$ | -0.053*** | -0.071*** | -0.078*** | -0.101*** |
| | (0.004) | (0.005) | (0.006) | (0.006) |
| Demographic controls | Yes | Yes | Yes | Yes |
| Reference group controls | Yes | Yes | Yes | Yes |
| Observations | 23,233 | 22,901 | 22,778 | 22,128 |
| | *Panel B. IV 2SLS* | | | |
| $\widehat{\Delta\bar{c}}_{-i,t}$ | -0.181 | 0.757** | 1.109*** | 0.946*** |
| | (0.416) | (0.329) | (0.339) | (0.294) |
| $\widehat{\Delta d_i}(c_{i,t-1}, c_{-i,t})$ | -0.093 | 0.256*** | 0.385*** | 0.500*** |
| | (0.152) | (0.080) | (0.088) | (0.173) |
| $\widehat{\Delta s_i}(c_{i,t-1}, c_{-i,t})$ | -17.548 | -0.267*** | -0.365*** | -0.490*** |
| | (1159.022) | (0.098) | (0.099) | (0.156) |
| Kleibergen Paap F-statistic ($\Delta d_i$) | 17.912 | 22.235 | 23.030 | 8.962 |
| Kleibergen Paap F-statistic ($\Delta s_i$) | 0.000 | 6.780 | 11.289 | 8.194 |
| Observations | 23,283 | 22,941 | 22,805 | 22,155 |
| Reference group FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes |

* significant at 10% ** significant at 5% *** significant at 1%. Small-case letters indicate logarithms. Dependent variable: $\Delta(c_{it})$ is household consumption growth. Inequality measures calculated with reference groups according to education-age-cohabitation. Each coefficient stems from a separate regression where the sample is restricted to individuals in a quartile of the income distribution of their reference group. Reference groups exclude individuals living in the same state. Demographic control variables are first differences of age, age-squared, years of education, no. of adults in household, no. of children in household, annual work hours, cohabitation. Reference group controls are the changes in the group averages of the demographic controls. Instrumented: $\Delta\bar{c}_{-i,t}$, $\Delta d_i(c_{i,t-1}, c_{-i,t})$, $\Delta s_i(c_{i,t-1}, c_{-i,t})$. Excluded instrument: $\Delta Windfall_{-i,t}$. Source: SOEP, v29.

age household increases consumption expenditure when the distance to others higher ranked in the expenditure distribution grows. Likewise, increases in the consumption distance to households ranked lower in the expenditure distribution leads to reduced consumption expenditures. Since exogenous variations in consumption disparity are related to household consumption, this behavior can not be explained by changes in expectations about future income as postulated by Hirschman (1973). Furthermore, estimation of the life cycle model by income quartile suggests that envious preferences are not an artifact of the log-normal shape of the consumption distribution. Conclusively, households are found to have envious and prideful preferences and choose consumption to catch up or stay ahead of others.

# Bibliography

**Alvarez-Cuadrado, Francisco, Jose Maria Casado, and Jose Maria Labeaga**, "Envy and Habits: Panel Data Estimates of Interdependent Preferences," *Oxford Bulletin of Economics and Statistics*, 2016, *78* (4), 443–469.

**Attanasio, Orazio and Hamish Low**, "Estimating Euler Equations," *Review of Economic Dynamics*, 2004, *7* (2), 405–435.

**Baum, Christopher F, Mark E Schaffer, and Steven Stillman**, "IVREG2: Stata module for extended instrumental variables/2SLS and GMM estimation," Statistical Software Components, Boston College Department of Economics April 2002.

**Browning, Martin and Thomas F. Crossley**, "Shocks, Stocks, and Socks: Smoothing Consumption over a Temporary Income Loss," *Journal of the European Economic Association*, December 2009, *6* (7), 1169–1192.

**Carroll, Christopher D. and Lawrence H. Summers**, "Consumption Growth Parallels Income Growth: Some New Evidence," in "National Saving and Economic Performance" NBER Chapters, National Bureau of Economic Research, Inc, January 1991, pp. 305–348.

**Clark, Andrew E and Claudia Senik**, "Who compares to whom? the anatomy of income comparisons in europe," *The Economic Journal*, 2010, *120* (544), 573–594.

**Cole, Harold L., George J. Mailath, and Andrew Postlewaite**, "Social Norms, Savings Behavior, and Growth," *Journal of Political Economy*, 1992, *100* (6), 1092–1125.

**Drechsel-Grau, Moritz and Kai D. Schmid**, "Consumption–savings decisions under upward-looking comparisons," *Journal of Economic Behavior & Organization*, 2014, *106*, 254 – 268.

**Duesenberry, James H.**, *Income, Saving and the Theory of Consumer Behavior*, Harvard University Press Cambridge, 1949.

**Dynan, Karen E.**, "Habit Formation in Consumer Preferences: Evidence from Panel Data," *American Economic Review*, June 2000, *90* (3), 391–406.

**Fehr, Ernst and Klaus M Schmidt**, "A theory of fairness, competition, and cooperation," *The Quarterly Journal of Economics*, 1999, *114* (3), 817–868.

**Hirschman, Albert O**, "The changing tolerance for income inequality in the course of economic development," *World Development*, 1973, pp. 544–566.

**Kleibergen, Frank and Richard Paap**, "Generalized reduced rank tests using the singular value decomposition," *Journal of Econometrics*, 2006, *133* (1), 97 – 126.

**Kuhn, Peter, Peter Kooreman, Adriaan Soetevent, and Arie Kapteyn**, "The Effects of Lottery Prizes on Winners and Their Neighbors: Evidence from the Dutch Postcode Lottery," *American Economic Review*, August 2011, *101* (5), 2226–47.

**Luttmer, Erzo F. P.**, "Neighbors as Negatives: Relative Earnings and Well-Being," *The Quarterly Journal of Economics*, 2005, *120* (3), 963–1002.

**MaCurdy, Thomas E.**, "The use of time series processes to model the error structure of earnings in a longitudinal data analysis," *Journal of Econometrics*, 1982, *18* (1), 83–114.

**Manski, Charles F.**, "Identification of Endogenous Social Effects: The Reflection Problem," *The Review of Economic Studies*, 1993, *60* (3), 531–542.

**Maurer, Jürgen and André Meier**, "Smooth it Like the 'Joneses'? Estimating Peer-Group Effects in Intertemporal Consumption Choice*," *The Economic Journal*, 2008, *118* (527), 454–476.

**Muellbauer, John**, "Habits, Rationality and Myopia in the Life Cycle Consumption Function," *Annals of Economics and Statistics*, 1988, *9* (9), 47–70.

**Ravina, Enrichetta**, "Habit Formation and Keeping Up with the Joneses: Evidence from Micro Data," *New York University Stern School of Business Working Paper*, 2008.

**Smith, Adam**, *The Theory of Moral Sentiments*, Clarendon Press. Oxford University Press, New York, NY, 1759.

**Veblen, Thorstein**, *The Theory of the Leisure Class: An Economic Study of Institutions*, Macmillan. New York, NY, 1899.

**Yitzhaki, Shlomo**, "Relative Deprivation and the Gini Coefficient: Reply," *The Quarterly Journal of Economics*, 1980, *95* (3), 575–576.

# Appendix A

## Derivation of equation (1.2)

The utility function with interdependent preferences of F&S is given by equation (1.1). Assume of the $n$ individuals in the society, $k-1$ individuals are poorer or at least as rich and $n-k$ individuals richer than $i$. Add and subtract $\beta_i \mu_i(x_{-i}) = \beta_i (n-1)^{-1} \sum_{j \neq i} x_j$ on the right. Equation (1.1) can be rearranged so that

$$
\begin{aligned}
U_i(x) =& x_i + \alpha_i \frac{1}{n-1} \sum_{j \neq i} \max\{x_j - x_i, 0\} + \beta_i \frac{1}{n-1} \sum_{j \neq i} \max\{x_i - x_j.0\} + \\
&+ \beta_i \frac{1}{n-1} \sum_{j \neq i} x_j - \beta_i \frac{1}{n-1} \sum_{j \neq i} x_j \\
=& x_i + \alpha_i \frac{1}{n-1} \sum_{j \neq i} \max\{x_j - x_i, 0\} - \beta_i \frac{1}{n-1} \sum_{j \neq i} x_j + \\
&+ \beta_i \frac{1}{n-1} \left[ (k-1)x_i - \sum_{\substack{j \neq i \\ x_i > x_j}} x_j + \sum_{j \neq i} x_j \right] \\
=& x_i + \alpha_i \frac{1}{n-1} \sum_{j \neq i} \max\{x_j - x_i, 0\} + \\
&+ \beta_i \frac{1}{n-1} \left[ (k-1)x_i + \sum_{\substack{j \neq i \\ x_i < x_j}} x_j \right] - \beta_i \frac{1}{n-1} \sum_{j \neq i} x_j \\
=& x_i + \alpha_i \frac{1}{n-1} \sum_{j \neq i} \max\{x_j - x_i, 0\} - \beta_i \frac{1}{n-1} \sum_{j \neq i} x_j + \\
&+ \beta_i \frac{1}{n-1} \left[ n x_i - (n-k+1)x_i + \sum_{\substack{j \neq i \\ x_i < x_j}} x_j \right]
\end{aligned}
\tag{A.1}
$$

In the last equation of (A.1), the term $\beta_i x_i n (n-1)^{-1}$ is added and subtracted. Rearranging gives (A.2) where $\max\{x_j - x_i, 0\} = (\sum_{x_i < x_j} x_j) - (n-k+1)x_i$

$$
\begin{aligned}
U_i(x) =& x_i + (\alpha_i + \beta_i) \frac{1}{n-1} \sum_{j \neq i} \max\{x_j - x_i, 0\} + \\
&+ \beta_i \frac{n}{n-1} x_i - \beta_i \frac{1}{n-1} \sum_{j \neq i} x_j .
\end{aligned}
\tag{A.2}
$$

Furthermore, note as the number of individuals goes to infinity,

$$\lim_{n\to\infty}\frac{n}{n-1}=1 \quad \text{and} \quad \lim_{n\to\infty}\mu_i(x_{-i})=\lim_{n\to\infty}\frac{1}{n-1}\sum_{j\neq i}x_j=\frac{1}{n}\sum_j x_j=\mu,$$

where $\mu$ is the mean income in the society. For large $n$, equation (A.2) is approximately identical to

$$U_i(x)=-\beta_i\mu+(1+\beta_i)x_i+(\alpha_i+\beta_i)\frac{1}{n-1}\sum_{j\neq i}\max\{x_j-x_i,0\} \tag{A.3}$$

## Proof of positive covariance between mean reference income and disadvantageous income inequality for non-degenerate income distributions

The covariance of $\mu(x_{-i})$ and $D_i(x)$ can be rearranged as follows.

$$\begin{aligned}\mathrm{Cov}[\mu(x_{-i}),D_i(x)] &= \mathrm{E}\Big[\Big(\mu(x_{-i})-\mathrm{E}[\mu(x_{-i})]\Big)\Big(D_i(x)-\mathrm{E}[D_i(x)]\Big)\Big]\\ &= \mathrm{E}\Big[\Big(\mu(x_{-i})-\mu(x)\Big)\Big(D_i(x)-D(x)\Big)\Big]\\ &= \mathrm{E}\Big[\mu(x_{-i})D_i(x)\Big],\end{aligned} \tag{A.4}$$

since both $\mu(x)$ and $D(x)$ are constant $\forall i \in N$. For every $i \in N$:

- $x_i \geq \mu(x) \implies \mu(x_{-i}) \leq \mu(x) \wedge D_i(x) \leq D(x)$
- $x_i < \mu(x) \implies \mu(x_{-i}) > \mu(x) \wedge D_i(x) > D(x)$

Thus, for non-degenerate income distributions, $\mathrm{Cov}\Big[\mu(x_{-i}),D_i(x)\Big]>0$.

# Appendix B

Table B.1: Poverty alleviation programs (BLP, DFA, IRDP) during the 1980s.

| Year | Policy | Regulation |
|---|---|---|
| 1979 | BLP-1 | New bank branches directed to districts with more than 20,000 people per bank branch |
| | IRDP | Financial assistance unified across all blocks |
| 1982 | BLP-2 | New bank branches directed to districts with more than 17,000 people per bank branch |
| 1983 | DFA-1 | Target of 15% (proportion of total outstanding credit loaned as direct finance to agriculture) to be reached by March 1985 |
| 1985 | DFA-2 | Target of 16% (proportion of total outstanding credit loaned as direct finance to agriculture) to be reached by March 1987 |
| | BLP-3 | New bank branches directed to districts with more than 17,000 people per bank branch |
| | IRDP | Financial assistance split such that 50% of the allocation received is based on poverty level at the block |
| 1987 | DFA-3 | Target of 18% (proportion of total outstanding credit loaned as direct finance to agriculture) to be reached by March 1990 |
| | IRDP | Financial assistance based entirely on poverty level at the block |
| 1989 | BLP-3 SAA | Blocks of 15-25 villages assigned to specific banks under a service area approach |

Table B.2: Variable source and construction.

| Variable | Source | Notes |
|---|---|---|
| | | *Panel A: Finance* |
| Rural bank branches | RBI-BSR | Number of rural bank branches in a district. Based on end of year (December) records. |
| Population to bank branch ratio | RBI-BSR, India Census | District-wise rural population (in 1981) divided by the number of rural bank branches in that district. |
| $Deficit$ | Policy | A district is classified as $deficit$ if its population to bank branch ratio at the onset of the BLP is higher then the stipulated target (20,000 for BLP-1 (1979-82), revised to 17,000 for BLP-2 (1982-85) and BLP-3 (1985-88)). If $deficit$, this variable takes value 1 and 0 otherwise. |
| | | *Panel B: Agriculture* |
| Output: | | |
| Yield | VDSA | Yield = $\frac{Quantity \times Price}{Area}$ $(Rs./ha)$. Our indicator is aggregated to include 15 crops$^{\dagger}$. Prices are deflated using all-India CPI with 1990 base year. |
| Production | VDSA | Production = $Quantity \times Price$ $(Rs.)$. Our indicator is aggregated to include 15 crops$^{\dagger}$. Prices are deflated using all-India CPI with 1990 base year. |
| Inputs: | | |
| Gross cropped area (GCA) | VDSA | Aggregate area $(ha)$ grown with 15 crops$^{\dagger}$. |
| Gross irrigated area (GIA) | VDSA | Aggregate area $(ha)$ of the 15 crops$^{\dagger}$ which is irrigated. |
| Share of HYV | VDSA | Share of GCA (of 15 crops) cultivated with HYVs$^{\S}$ (%). |
| Nitrogen fertilizer | VDSA | Consumption measured in tons per hectare $(tons/ha)$. |
| Potassium fertilizer | VDSA | Consumption measured in tons per hectare $(tons/ha)$. |
| Phosphate fertilizer | VDSA | Consumption measured in tons per hectare $(tons/ha)$. |
| Pumps | VDSA | Number of pumps recorded (‘000). |
| Tractors | VDSA | Number of pumps recorded (‘000). |
| Crop choice: | | |
| High-volatility | VDSA | Share of GCA (of 15 crops) grown with crops having above average relative yield volatility. Yield volatility is measured per crop at the State level, with data from 1968 to 2000, using a coefficient of variation. |
| Rain-sensitive | VDSA | Share of GCA (of 15 crops) grown with crops having an above than average effect from rainfall. This is measured using the t-statistic value from individual regressions of crop yield on annual rainfall at the State level (with data from 1968 to 2000). |
| Cash-crops | VDSA | Share of GCA (of 15 crops) grown with cash crops (cotton, sugarcane, linseed, soya, groundnut, rapeseed and mustard). |
| Winter-crops | VDSA | Share of GCA (of 15 crops) grown with winter crops (barley, chickpea, linseed, mustard, rapeseed, sesame, soya, and wheat). |

$^{\dagger}$Fifteen crops include: barley, chickpea, cotton, finger millet, groundnut, linseed, maize, pearl millet, pigeon pea, rice, rape and mustard seed, sesame, sorghum, sugarcane, and wheat. $^{\S}$The five crops cultivated with HYVs include: rice, wheat, sorghum, maize, and pearl millet.

Table B.3: Impact of access to financial services on agricultural output and inputs: Removing outliers (1979-82, 1982-85, 1985-88).

| | Output | | Inputs | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Land | Irrigation | Seeds | Fertilizer | | | Machinery[a] | |
| *Growth in*: | Yield (1) | Production (2) | GCA (3) | GIA (4) | HYV (5) | Nitrogen (6) | Potassium (7) | Phosphate (8) | Pumps (9) | Tractors (10) |
| *Panel A: Bank Growth (IV-TSLS)* | | | | | | | | | | |
| Bank Growth | 0.409*** | 0.456*** | 0.055 | 0.094 | 0.484*** | -0.138 | 0.559 | -0.388 | -0.357 | 0.095 |
| | (0.151) | (0.174) | (0.050) | (0.112) | (0.177) | (0.313) | (0.420) | (0.607) | (0.427) | (0.631) |
| Kleibergen-Paap F-statistic | 35.961 | 35.961 | 35.961 | 35.961 | 35.961 | 35.961 | 35.961 | 35.961 | 19.343 | 19.291 |
| *Panel B: Interaction of Bank Growth and Lag Rainfall (IV-TSLS)* | | | | | | | | | | |
| Bank Growth | 0.270 | 0.232 | 0.002 | -0.082 | 0.572** | -0.139 | -0.135 | -0.440 | 0.083 | -0.395 |
| | (0.212) | (0.238) | (0.049) | (0.117) | (0.225) | (0.261) | (0.420) | (0.498) | (1.316) | (1.018) |
| Bank Growth × Lag Rainfall | -3.240*** | -3.776*** | -0.083 | -1.426*** | -0.428 | -0.841 | -0.921 | 0.194 | 1.880 | -1.137 |
| | (0.950) | (1.267) | (0.138) | (0.305) | (0.614) | (0.870) | (0.946) | (0.996) | (5.139) | (3.297) |
| Lag Rainfall | 1.377*** | 1.676** | 0.079* | 0.535*** | 0.337* | -0.085 | -0.174 | -0.790* | -1.507 | -1.817* |
| | (0.512) | (0.690) | (0.041) | (0.128) | (0.179) | (0.308) | (0.383) | (0.429) | (1.726) | (0.988) |
| Kleibergen-Paap F-statistic | 19.242 | 19.242 | 19.242 | 19.242 | 19.242 | 19.242 | 19.242 | 19.242 | 8.932 | 9.465 |
| Observations | 575 | 575 | 575 | 575 | 575 | 575 | 575 | 575 | 298 | 292 |
| Districts | 197 | 197 | 197 | 197 | 197 | 197 | 197 | 197 | 184 | 184 |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State Time Trend | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates for Panel A are based on the model outlined in equation (2.3), and equation (2.4) for Panel B. Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on our three instruments. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level. Controls include growth in annual rainfall. For a description of each variable source and construction, refer to Table B.2.[a]Availability of data for machinery is limited to growth in the first two BLPs (1979-82, 1982-85).

Table B.4: Impact of access to financial services on agricultural output and inputs: Prior to IRDP (1979-82, 1982-85).

| | Output | | Inputs | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Land | Irrigation | Seeds | Fertilizer | | | Machinery[a] | |
| *Growth in*: | Yield (1) | Production (2) | GCA (3) | GIA (4) | HYV (5) | Nitrogen (6) | Potassium (7) | Phosphate (8) | Pumps (9) | Tractors (10) |
| *Panel A: OLS* | | | | | | | | | | |
| Bank Growth | 0.019 | -0.002 | -0.022 | 0.050 | 0.220 | 0.046 | -0.066 | -0.031 | 1.760 | -0.207 |
| | (0.051) | (0.059) | (0.023) | (0.037) | (0.201) | (0.067) | (0.088) | (0.098) | (1.386) | (0.331) |
| *Panel B: IV-TSLS* | | | | | | | | | | |
| Bank Growth | 0.315** | 0.320** | 0.011 | 0.180 | 0.346* | 0.256 | 0.522 | 0.151 | -0.285 | 0.150 |
| | (0.138) | (0.155) | (0.059) | (0.124) | (0.188) | (0.228) | (0.334) | (0.271) | (0.414) | (0.602) |
| Kleibergen-Paap F-statistic | 24.815 | 24.815 | 24.815 | 24.815 | 24.815 | 24.815 | 24.815 | 24.815 | 18.188 | 18.188 |
| Observations | 431 | 431 | 431 | 431 | 431 | 431 | 431 | 431 | 321 | 321 |
| Districts | 218 | 218 | 218 | 218 | 218 | 218 | 218 | 218 | 204 | 204 |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State Time Trend | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates are based on the model outlined in equation 2.3. Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on our three instruments. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level. Controls include growth in annual rainfall. For a description of each variable source and construction, refer to Table B.2.[a]Availability of data for machinery is limited to growth in the first two BLPs (1979-82, 1982-85).

Table B.5: Impact of access to financial services on crop choice: Removing outliers (1979-82, 1982-85, 1985-88).

| *Growth in* (*Area* − *Share*): | High-Volatility (1) | Rain-Sensitive (2) | Cash-Crops (3) | Winter-crops (4) |
|---|---|---|---|---|
| *Panel A: Bank Growth (IV-TSLS)* | | | | |
| Bank Growth | 0.181 | -0.118 | 0.388** | 0.387*** |
| | (0.317) | (0.118) | (0.180) | (0.144) |
| Kleibergen-Paap F-statistic | 35.917 | 36.240 | 36.053 | 36.087 |
| *Panel B: Interaction of Bank Growth and Lag Rainfall (IV-TSLS)* | | | | |
| Bank Growth | 0.269 | -0.125 | 0.308* | 0.463*** |
| | (0.293) | (0.113) | (0.178) | (0.163) |
| Bank Growth × Lag Rainfall | 0.732 | -0.278 | -0.295 | -1.119** |
| | (0.621) | (0.216) | (0.456) | (0.506) |
| Lag Rainfall | -0.282 | -0.032 | -0.259 | 0.539** |
| | (0.272) | (0.063) | (0.161) | (0.243) |
| Kleibergen-Paap F-statistic | 19.217 | 19.624 | 19.426 | 19.522 |
| Observations | 574 | 568 | 573 | 570 |
| Districts | 197 | 194 | 196 | 195 |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| State Time Trend | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates for panel A are based on the model outlined in equation (2.3), and equation (2.4) for panel B. Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on our three instruments. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level. For a description of each variable source and construction, refer to Table B.2.

Table B.6: Impact of access to financial services on crop choice: Prior to IRDP (1979-82, 1982-85).

| *Growth in (Area share of)*: | High-Volatility (1) | Rain-Sensitive (2) | Cash-Crops (3) | Winter-Crops (4) |
|---|---|---|---|---|
| | *Panel A: OLS* | | | |
| Bank Growth | -0.015 | 0.032 | -0.120 | -0.011 |
| | (0.049) | (0.033) | (0.097) | (0.036) |
| | *Panel B: IV-TSLS* | | | |
| Bank Growth | -0.277 | -0.127 | 0.222 | 0.361** |
| | (0.315) | (0.144) | (0.230) | (0.160) |
| Kleibergen-Paap F-statistic | 31.712 | 31.725 | 31.712 | 31.742 |
| Observations | 431 | 427 | 431 | 429 |
| Districts | 218 | 215 | 217 | 216 |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| State Time Trend | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |

Notes: * significant at 10% ** significant at 5% *** significant at 1%. Estimates are based on model outlined in equation (2.3). Standard errors are clustered at the district level and reported in parentheses. The F-statistics reported is a joint test on our three instruments. Data on 218 districts. Variation in observations are due to missing data on any one of the variables at the district year level. For a description of each variable source and construction, refer to Table B.2.

# Appendix C

## Simplifying the FOC

This Appendix shows that under constant return on wealth and static expectations on the consumption distribution, such that $\mathbb{E}_t[F_{t+1}(c_{it})] = \mathbb{E}_t[F_s(c_{is+1})]$ for $s = t+2, ..., T-1$, the first order condition can be simplified. The proof is borrowed from Hayashi (1985), in which consumption services are modeled as a distributed lag function of current and past expenditures. It needs to be shown that the first order condition derived with internal and external habits given by

$$\delta(1+r)\frac{exp(\xi'\mathbf{x_{it+1}})(\tilde{c}_{it+1})^{-\sigma} + \delta\kappa_{it+1}exp(\xi'\mathbf{x_{it+2}})(\tilde{c}_{it+2})^{-\sigma}}{exp(\xi'\mathbf{x_{it}})(\tilde{c}_{it})^{-\sigma} + \delta\kappa_{it}exp(\xi'\mathbf{x_{it+1}})(\tilde{c}_{it+1})^{-\sigma}} = 1 + e_{it+1}, \tag{C.1}$$

implies

$$\delta(1+r)\frac{exp(\xi'\mathbf{x_{it+1}})(\tilde{c}_{it+1})^{-\sigma}}{exp(\xi'\mathbf{x_{it}})(\tilde{c}_{it})^{-\sigma}} = 1 + e_{it+1}. \tag{C.2}$$

Let $MU_{it+s} = \partial u_i(\tilde{c}_{it+s})/\partial \tilde{c}_{it+s}$, for $s = 1, 2, , ..., T-t$, represent the partial derivative of current utility with respect to current consumption services. Rewrite equation (C.1) in terms of conditional expectations and rearrange

$$\begin{aligned}
\delta(1+r)\mathbb{E}_t\Big[\frac{MU_{it+1} + \delta\kappa_{it+1}MU_{it+2}}{MU_t + \delta\kappa_{it}MU_{t+1}}\Big] &= 1 \\
\delta(1+r)\mathbb{E}_t[MU_{it+1} + \delta\kappa_{it+1}MU_{it+2}] &= \mathbb{E}_t[MU_t + \delta\kappa_{it}MU_{t+1}] \\
\mathbb{E}_t[(\delta(1+r)MU_{t+1} - MU_t) + \delta\kappa_{it}((1+r)MU_{t+2} - MU_{t+1})] &= 0
\end{aligned} \tag{C.3}$$

where the last equality follows from

$$\begin{aligned}
\mathbb{E}_t[\kappa_{it+1}] =& \mathbb{E}_t[\alpha - (\alpha+\beta)F_{t+2}(c_{it+1}) - \theta] \\
=& \alpha - (\alpha+\beta)\mathbb{E}_t[F_{t+2}(c_{it+1})] - \theta \\
=& \alpha - (\alpha+\beta)\mathbb{E}_t[F_{t+1}(c_{it})] - \theta \\
=& \mathbb{E}_t[\kappa_{it}],
\end{aligned} \tag{C.4}$$

since all households smooth consumption and do not anticipate changes to the consumption distribution $\mathbb{E}_t[F_{t+2}(c_{it+1})] = \mathbb{E}_t[F_{t+1}(c_{it})]$. Let

$$_ty_{it+k} = \mathbb{E}_t[\delta(1+r)MU_{it+k+1} - MU_{it+k}] \tag{C.5}$$

so that equation (C.3) becomes

$$_ty_{it} + \delta\mathbb{E}_t[\kappa_{it}]_ty_{it+1} = 0. \tag{C.6}$$

Condition (C.6) holds throughout life, which implies

$$_sy_{is} + \delta\mathbb{E}_s[\kappa_{is}]_sy_{is+1} = 0, \qquad s = t, t+1, ..., T-1 \tag{C.7}$$

and $_sy_{iT} = -\mathbb{E}_s[MU_{iT}]$. Applying the expectations operator at time $t$ to equation (C.7) yields

$$_ty_{is} + \delta\mathbb{E}_t[\kappa_{is}]_ty_{is+1} = 0, \qquad s = t, t+1, ..., T-1 \tag{C.8}$$

Now substituting $x_{i\tau} =_t y_{it+\tau}$ into equation (C.8) gives

$$x_{is-t} + \delta\mathbb{E}_t[\kappa_{is}]x_{is-t+1} = 0 \tag{C.9}$$

Equation (C.9) is a non-autonomous first-order difference equation in $x_i$, which can be solved by iteration such that $x_{is-t+1} = \prod_{j=0}^{s-t}[(-1/(\delta\mathbb{E}_t[\kappa_{ij}]))x_{i0}]$. Under the assumptions $0 < \delta < 1$ and $|\mathbb{E}_t[\kappa_{is}]| < 1/\delta$, for $s = t, t+1, ..., T-1$, the equation is divergent and $x_{i0}$ is small relative to the terminal value[12]. The first assumption is standard in the literature and implied by the stronger assumption of large discount rates. The second assumption places boundaries on $\alpha$ and $\beta$. Since $F_s \in [0, 1]$, this assumption can be restated

$$|\beta| < 1/\delta \quad \text{and} \quad |\alpha| < 1/\delta, \tag{C.10}$$

The existence of an equilibrium requires small values for $\alpha$ and $\beta$. The discount rate is assumed to be large so that windfall shocks affect current period consumption. Taken together, these factors suggest that the second assumption is fulfilled. Since the difference equation is unstable, the initial value $x_{i0}$ must be small relative to the

[12] A third assumption, $\mathbb{E}_t[\kappa_{is}] \neq 0$, is implied directly. If it is violated, the result follows immediately from equation (C.1).

terminal value. If $T \rightarrow \infty, x_{i0} = 0$, implying that

$$\delta(1+r)\frac{exp(\xi'\mathbf{x_{it+1}})(\tilde{c}_{it+1})^{-\sigma}}{exp(\xi'\mathbf{x_{it}})(\tilde{c}_{it})^{-\sigma}} = 1 + e_{it+1}. \tag{C.11}$$

Table C.1: Heterogeneity analysis by income quartile in the sample income distribution. Reference groups by occupation-age-cohabitation.

| | Income quartile | | | |
|---|---|---|---|---|
| Dependent variable: $\Delta c_{i,t}$ | $1^{st}$ quartile | $2^{nd}$ quartile | $3^{rd}$ quartile | $4^{th}$ quartile |
| *Panel A. OLS* | | | | |
| $\Delta\bar{c}_{-i,t}$ | 0.147*** | 0.032 | 0.029 | -0.059 |
| | (0.055) | (0.043) | (0.036) | (0.042) |
| $\Delta d_i(c_{i,t-1}, c_{-i,t})$ | 0.047*** | 0.034*** | 0.026*** | 0.022*** |
| | (0.014) | (0.007) | (0.004) | (0.004) |
| $\Delta s_i(c_{i,t-1}, c_{-i,t})$ | -0.048*** | -0.055*** | -0.065*** | -0.080*** |
| | (0.005) | (0.004) | (0.003) | (0.004) |
| Demographic controls | Yes | Yes | Yes | Yes |
| Reference group controls | Yes | Yes | Yes | Yes |
| Observations | 7,451 | 11,833 | 15,376 | 17,895 |
| *Panel B. IV 2SLS* | | | | |
| $\hat{\Delta}\bar{c}_{-i,t}$ | -0.452 | 0.220 | 0.246 | 0.575*** |
| | (0.558) | (0.253) | (0.155) | (0.206) |
| $\hat{\Delta} d_i(c_{i,t-1}, c_{-i,t})$ | 0.371 | 0.054 | 0.079** | 0.155*** |
| | (1.429) | (0.085) | (0.039) | (0.043) |
| $\hat{\Delta} s_i(c_{i,t-1}, c_{-i,t})$ | 0.007 | -0.064 | -0.078* | -0.183*** |
| | (0.170) | (0.130) | (0.042) | (0.052) |
| Kleibergen Paap F-statistic ($\Delta d_i$) | 0.083 | 13.495 | 35.130 | 33.130 |
| Kleibergen Paap F-statistic ($\Delta s_i$) | 1.492 | 2.338 | 24.581 | 28.025 |
| Observations | 7,774 | 12,064 | 15,646 | 18,085 |
| Reference group FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes |

* significant at 10% ** significant at 5% *** significant at 1%. Small-case letters indicate logarithms. Dependent variable: $\Delta(c_{it})$. Inequality measures calculated with reference groups according to education-age-cohabitation. Each coefficient stems from a separate regression where the sample is restricted to individuals in a quartile of the income distribution. Reference groups exclude individuals living in the same state. Demographic control variables are first differences of age, age-squared, years of education, no. of adults in household, no. of children in household, indicator for repeated survey completion, annual work hours, cohabitation. Reference group controls are the changes in the group averages of the demographic controls. Instrumented: $\Delta\bar{c}_{-i,t}$, $\Delta d_i(c_{i,t-1}, c_{-i,t})$, $\Delta s_i(c_{i,t-1}, c_{-i,t})$. Excluded instrument: $\Delta Windfall_{-i,t}$. Source: SOEP, v29.

Table C.2: Heterogeneity analysis by income quartile in the sample income distribution. Reference groups by education-age-cohabitation.

| | Income quartile | | | |
|---|---|---|---|---|
| Dependent variable: $\Delta c_{i,t}$ | $1^{st}$ quartile | $2^{nd}$ quartile | $3^{rd}$ quartile | $4^{th}$ quartile |
| *Panel A. OLS* | | | | |
| $\Delta\bar{c}_{-i,t}$ | 0.058 | 0.085 | -0.007 | -0.068 |
| | (0.058) | (0.057) | (0.054) | (0.102) |
| $\Delta d_i(c_{i,t-1}, c_{-i,t})$ | 0.081*** | 0.029*** | 0.028*** | 0.027*** |
| | (0.010) | (0.008) | (0.005) | (0.004) |
| $\Delta s_i(c_{i,t-1}, c_{-i,t})$ | -0.047*** | -0.073*** | -0.079*** | -0.093*** |
| | (0.004) | (0.004) | (0.004) | (0.005) |
| Demographic controls | Yes | Yes | Yes | Yes |
| Reference group controls | Yes | Yes | Yes | Yes |
| Observations | 20,721 | 22,984 | 23,337 | 23,998 |
| *Panel B. IV 2SLS* | | | | |
| $\hat{\Delta}\bar{c}_{-i,t}$ | 1.077** | -0.216 | 0.775** | 0.784*** |
| | (0.492) | (0.437) | (0.336) | (0.281) |
| $\hat{\Delta}d_i(c_{i,t-1}, c_{-i,t})$ | 0.471*** | 0.009 | 0.198*** | 0.487** |
| | (0.155) | (0.087) | (0.058) | (0.213) |
| $\hat{\Delta}s_i(c_{i,t-1}, c_{-i,t})$ | -1.753 | 0.062 | -0.240*** | -0.353*** |
| | (4.073) | (0.363) | (0.087) | (0.098) |
| Kleibergen Paap F-statistic ($\Delta d_i$) | 18.936 | 26.780 | 34.240 | 5.713 |
| Kleibergen Paap F-statistic ($\Delta s_i$) | 0.169 | 0.682 | 9.779 | 15.328 |
| Observations | 20,776 | 23,018 | 23,361 | 24,029 |
| Reference group FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes |

* significant at 10% ** significant at 5% *** significant at 1%. Small-case letters indicate logarithms. Dependent variable: $\Delta(c_{it})$. Inequality measures calculated with reference groups according to education-age-cohabitation. Each coefficient stems from a separate regression where the sample is restricted to individuals in a quartile of the income distribution. Reference groups exclude individuals living in the same state. Demographic control variables are first differences of age, age-squared, years of education, no. of adults in household, no. of children in household, indicator for repeated survey completion, annual work hours, cohabitation. Reference group controls are the changes in the group averages of the demographic controls. Instrumented: $\Delta\bar{c}_{-i,t}$, $\Delta d_i(c_{i,t-1}, c_{-i,t})$, $\Delta s_i(c_{i,t-1}, c_{-i,t})$. Excluded instrument: $\Delta Windfall_{-i,t}$. Source: SOEP, v29.